VIVES
RESEARCH CENTER FOR REGIONAL ECONOMICS

VIVES DISCUSSION PAPER

N° 60
OCTOBER 2017

Productivity Growth Over the Business Cycle: Cleansing Effects of Recessions

Jeroen Van den bosch
VIVES (KU Leuven)

Stijn Vanormelingen
ECON (KU Leuven, campus Brussels)

KU LEUVEN

Productivity Growth Over the Business Cycle: Cleansing Effects of Recessions*

Van den bosch, J.,[†] Vanormelingen, S.[‡]

October 2017

Abstract

Using recent productivity decomposition methods, we provide new insights on the impact of recent recessions on the micro origins of aggregate productivity growth for a small, open and developed economy, Belgium. We use a dataset that includes both manufacturing and services industries for the period 1997-2014. The empirical framework discerns between incumbents, entering and exiting firms and provides insights on productivity dynamics within each of these groups. We find evidence on cleansing effects of recessions. This cleansing effect is more outspoken in manufacturing industries compared to services industries. Furthermore, our results indicate that entering and exiting firms underperform on average compared to incumbent firms and that job allocation and productivity are best aligned in exiting firms and worst aligned in entering firms.

Keywords: Aggregate productivity; Business Cycles; Cleansing effects
JEL classification: L25; E32; D22

*We are grateful to Joep Konings and Sašo Polanec for helpful comments and suggestions. We also acknowledge the insightful comments that we received at the 2017 EEA Conference, the 2017 ECORES conference and the VIVES seminar series. All remaining errors are our own responsibility.

†Department of Economics - VIVES, KU Leuven, Belgium (e-mail: jeroen.vandenbosch@kuleuven.be)

‡Department of Economics - KU Leuven, campus Brussels, Belgium (e-mail: stijn.vanormelingen@kuleuven.be)

1 Introduction

Productivity growth is not everything, but in the long run it is almost everything (Krugman, 1994). Gains in productivity, or the efficiency with which inputs are turned into outputs, account for a substantial fraction of cross country differences in income.[1] Therefore, understanding the evolution of aggregate productivity is a central topic in economics that has received particular theoretical and empirical attention.

Over the last decades, empiricists showed that the macroeconomic idea of one representative firm does not tally with reality. Instead, there is tremendous heterogeneity in productivity between firms, even within narrowly defined industries (Syverson, 2004). This heterogeneity induces several mechanisms at the micro level. Research on micro channels of aggregate productivity growth established both theoretically and empirically the importance of *efficient allocation of resources*, next to *within* firm productivity growth. Bartelsman et al. (2004) and Pages et al. (2009) find within firm productivity growth to be the most important source of aggregate productivity growth for a large sample of countries. However, Mitsukuni et al. (2014) show that their findings could be an artifact of the decomposition methods they used. They find that growth from resource reallocation is robust and consistent over time. In line with their findings, Van Beveren and Vanormelingen (2014) show that in Belgium resource reallocation is the most stable determinant of aggregate productivity growth. Also Bartelsman et al. (2013) and Olley and Pakes (1996) show that the covariance between size and productivity plays a key role in the aggregate productivity evolution. Furthermore Collard-Wexler et al. (2011), Banerjee and Moll (2010) and Restuccia and Rogerson (2008) find efficient allocation of resources to account for a large part of aggregate productivity variations. The objective of this paper is to assess the impact of recent recessions on these micro channels. In this paper we answer the following questions: Did recent recessions have a “cleansing effect”, i.e. was productivity growth from resource reallocation higher in recession periods than in non-recession periods? How

[1] The relation between the evolution in GDP per capita and productivity is well established, see the work of Gordon (2016), Jones and Romer (2010), Caselli (2005), Basu and Fernald (2002), Easterly and Levine (2001), Hall and Jones (1999), Dowrick and Nguyen (1989) amongst others.

do these micro channels in entering and exiting firms compare to incumbents in recession versus non-recession periods? How do manufacturing and services industries differ in realizing productivity growth over the business cycle?

The idea that recession periods give rise to more efficient resource allocation dates back to the work of Schumpeter (1939), who advanced the argument that recessions induce productivity enhancing reallocation by driving out unproductive investments and thereby freeing up resources for more productive uses. Caballero and Hammour (1994) developed a formal model that incorporates the *cleansing* of less efficient production arrangements such that more resources become available for production arrangements that are relatively more productive. The cleansing hypothesis suggests increased gross job reallocation during recessions from job destruction that is more procyclical than job creation. Davis and Haltiwanger (1992) and Konings (1995) found that recessions are indeed associated with countercyclical gross job reallocation. However, there is no ubiquitous evidence in the literature that this also results in countercyclical aggregate productivity growth (Baily et al., 2001). The literature proposes various factors that could distort the cleansing mechanism. Firms could do labor hoarding, which would lower productivity in recession periods. Also, recessions could affect plant level productivity negatively and this could in itself dominate the increase in aggregate productivity due to cleansing. Furthermore, Barlevy (2002) argues that recessions could have a sullying effect because they tend to slow down the matching of newly unemployed with high productive jobs. This would at least moderate the contribution from job reallocation to aggregate productivity. While there are mechanisms that could counteract the cleansing effect, there are others that are in line with countercyclical productivity growth. Aghion and Saint-Paul (1991) argue that firms engage in productivity-enhancing activities during economic downturns because of temporarily low opportunity costs in forgone profits. This would lead to countercyclical productivity. Altogether, it is not obvious a priori what will be the net effect of job reallocation on aggregate productivity in recession periods. Recently, Foster et al. (2015) picked up on this issue and found for the U.S. that the intensity of job reallocation during the recent great recession was relatively low and less productivity enhancing than in previous recessions.

Entry and *exit* also have an important role in aggregate productivity dynamics (Clementi and Palazzo, 2016). Micro-level studies find that entrants have, on average, lower productivity than incumbents because, for example, it can take some time for entrants to optimize their production processes. Moreover, entrants often set lower prices than incumbents to gain market share, which will result in lower revenue productivity levels (Foster et al., 2008). Over time however, the more productive firms in the entry cohorts survive and their productivity levels may converge to those of incumbent firms (Aw et al., 2001). Ouyang (2009) argues that recessions could have a *scarring* effect on entrants. Recessions are typically characterized by low demand and low profitability. For infant firms, this can be hard to overcome, resulting in high exit rates of young firms that probably would have survived in non-recession periods. Amongst these young exiting firms could be firms that would have become high productive incumbents later on in their life cycle. Therefore, the scarring effect of recessions could lead to lower aggregate productivity in the long run. Regarding the contribution of exit to aggregate productivity, the long run equilibrium model of Hopenhayn (1992) suggests that firms decide to exit when they face low individual productivity shocks. Hence exit of low productive firms contributes positively to aggregate productivity. Empirical studies affirm these theoretical predictions, for example Foster et al. (2001) and Aw et al. (2001) find this to be true for US and Taiwanese manufacturing. In recession periods, the probability that firms have low individual productivity shocks increases, thereby resulting in higher exit rates.

To measure the microeconomic drivers of productivity growth and the effect of recessions on these, we will rely on productivity decomposition models because these allow to infer how much of aggregate productivity growth can be explained by each of the aformentioned channels. More specifically, we apply the decomposition model of Melitz and Polanec (2015). They extended the static model of Olley and Pakes (1996) into a dynamic model that also includes entry and exit components. By relying on the cross-sectional distribution of market shares and productivity, their model allows natural counterfactuals for the entry and exit components. We complement the results from this model with the Foster et al. (2001) decomposition to learn how much of productivity growth is due to (re)allocation of resources.

This paper aims to understand how recession periods affect the micro origins of aggregate productivity growth in a small, open and developed economy, Belgium. To that aim, we use a representative sample of firms active in the Belgium private sector, including both manufacturing and services industries. This paper touches upon and contributes to several strands in the industrial organization literature. First, we compare the relative contributions from incumbent, entering and exiting firms to aggregate productivity growth. In line with expectations, we find that incumbent firms largely determine aggregate productivity growth. Second, we show aggregate productivity effects of job reallocation before, during and after recession periods. We find evidence of cleansing effects, so recession periods induce job reallocation towards the most productive firms. We also find that the contribution from job reallocation to aggregate productivity growth is higher on average and more stable than the contribution from within firm productivity growth, which is lower on average and more volatile. This is consistent with the findings of Van Beveren and Vanormelingen (2014). Third, we regard the productivity dynamics over the business cycle in entering and exiting firms. We find that average productivity in entering and exiting firms is generally lower than in incumbent firms. Moreover, job allocation and productivity are more aligned in the cross section of exiting firms than in the cross section of entering firms. Fourth and last, we investigate whether and to which extent each of these micro drivers of aggregate productivity growth are different between manufacturing and services industries. We find that productivity growth is lower in services sectors, and that the cleansing effect is far more pronounced in the manufacturing sector. Dynamics from entry and exit are relatively important determinants of aggregate productivity growth in services industries, while productivity growth within firms and job reallocation in incumbent firms largely determines aggregate productivity growth in manufacturing industries.

The remainder of this paper will be organized as follows: in the following section, we elucidate the empirical framework that will be used to compose aggregate productivity levels and decompose productivity growth from the macro level to its foundations on the micro level. The third section describes the data. The fourth section presents and discusses the results. The fifth section concludes by summarizing our main findings.

2 Empirical Framework

Since the productivity concept was introduced by Solow (1957) as the residual of an aggregate production function, many scholars tried to understand the micro origins of productivity growth at the aggregate level. Increasing availability of firm level data induced researchers to develop rigorous decomposition models. Such models typically distinguish three channels through which aggregate productivity growth can arise. A first channel consists of *incumbent* firms that succeed in moving their productivity frontier *(within)* or succeed in attracting market share from firms with lower productivity *(reallocation)*. A second potential driver of aggregate productivity growth is *entry* of high productive firms. A third potential channel is *exit* of low productive firms. Baily et al. (1992) were the first to propose a comprehensive model to disentangle the black box of aggregate productivity growth and to identify the contribution from each of these channels. Their model was criticized because the entry and exit components of their model are biased by construction. Therefore, Griliches and Regev (1995) and Foster et al. (2001, hereafter FHK) introduced modifications that improve on this issue. All these models rely on the evolution of the productivity level and market share of individual firms over time. Another strand of models relies on the mean and covariance of the joint distribution of productivity and market shares. The first model of this kind was introduced by Olley and Pakes (1996). Recently, Melitz and Polanec (2015, hereafter MP) developed the so-called dynamic Olley and Pakes decomposition which extends the static Olley and Pakes (1996) decomposition into a dynamic model that includes entry and exit.[2] The MP model does not suffer from the measurement bias which is present in decomposition models that rely on the firm level evolution of productivity and market share. Because of its attractive properties, we rely on the MP decomposition and complement it with the FHK model where necessary to answer the research questions.

[2]The Olley and Pakes (1996) decomposition is interesting in itself. It is a static decomposition that distinguishes the relative importance of technical efficiency versus optimal allocation of resources in aggregate productivity. The model we will use heavily relies on this decomposition. Nevertheless, a static approach does not allow to investigate the role of entry and exit, while this is elementary to the creative destruction concept of Schumpeter (1939) that underlies cleansing. Therefore we apply dynamic productivity decompositions, which investigate the evolution of productivity over time and include entering and exiting firms.

Like in most empirical work and productivity decompositions, aggregate productivity is defined as a weighted average of firm level productivity levels.[3] For the estimation of firm level productivity measures, we refer to section 3.2 and appendix B. In regard of the pursued research questions, we choose to aggregate firm level productivity measures using employment shares.[4,5] If aggregate productivity increases due to job reallocation during of right after recession periods, we conclude that the recession has a cleansing effect, i.e. recessions are associated with or result in employment shifts from low productivity towards high productivity firms.

The labor share of firm i in industry j at year t is indicated by ms_{ijt}. Aggregate productivity is defined as the weighted average of firm level productivity:

$$Prod_t = \sum_j \sum_i ms_{ijt} * prod_{ijt} \tag{1}$$

Since productivity is expressed in logs, aggregate productivity growth in percentages can then be obtained by:

$$\Delta Prod = Prod_t - Prod_{t-1} \tag{2}$$

The emphasis of our paper is on aggregate Total Factor Productivity (TFP). However, the methodology also applies to other productivity measures, e.g. labor productivity, for which we present some results in appendix A.2. We will use two specifications of the MP model. The first decomposition model is at the level of the economy and the second model extends the first into an industry decomposition. The derivation of each specification is included in appendix C. Equation (3) presents the final equation of the economy-wide decomposition:

[3] One notable exception is the decomposition model of Petrin and Levinsohn (2012) However, their model deviates by not incorporating separate terms for entering and exiting firms. Therefore, we do not regard their model.

[4] Aggregation of TFP measures was explored by Domar (1961) and further developed by Hulten (1978). They indicated the importance of netting out intra-industry flows of intermediary goods to avoid double counting of outputs on the aggregated level. More recently, Foster et al. (2001) and Van Biesebroeck (2008) discuss the various possibilities in choosing weighting shares to aggregate TFP measures and how this choice could affect the outcomes of TFP decompositions at the macro level. By choosing employment shares, we implicitly assume these weights represent the share of the firm in aggregate productivity.

[5] This is how we relate job (re)allocation at the micro level with the evolution of productivity at the macro level. Note that we do not track individuals that change jobs. Job reallocation must be understood as increasing or decreasing market shares in the labor market.

$$
\begin{aligned}
\Delta TFP = \quad & \underbrace{\overline{tfp}_{S2} - \overline{tfp}_{S1}}_{\Delta \overline{TFP}_{surv}} \\
& + \underbrace{\sum_i (ms_{iS2} - \overline{ms}_{S2})(tfp_{iS2} - \overline{tfp}_{S2}) - \sum_i (ms_{iS1} - \overline{ms}_{S1})(tfp_{iS1} - \overline{tfp}_{S1})}_{\Delta Cov(TFP, MS)_{surv}} \\
& + \underbrace{MS_{E2}\left[\overline{tfp}_{E2} - \overline{tfp}_{S2}\right]}_{\overline{TFP}_{entr_t - surv_t}} \\
& + \underbrace{MS_{E2}\left[\sum_i (ms_{iE2} - \overline{ms}_{E2})(tfp_{iE2} - \overline{tfp}_{E2}) - \sum_i (ms_{iS2} - \overline{ms}_{S2})(tfp_{iS2} - \overline{tfp}_{S2})\right]}_{Cov(TFP, MS)_{entr_t - surv_t}} \qquad (3) \\
& + \underbrace{MS_{X1}\left[\overline{tfp}_{S1} - \overline{tfp}_{X1}\right]}_{\overline{TFP}_{surv_{t-1} - exit_{t-1}}} \\
& + \underbrace{MS_{X1}\left[\sum_i (ms_{iS1} - \overline{ms}_{S1})(tfp_{iS1} - \overline{tfp}_{S1}) - \sum_i (ms_{iX1} - \overline{ms}_{X1})(tfp_{iX1} - \overline{tfp}_{X1})\right]}_{Cov(TFP, MS)_{surv_{t-1} - exit_{t-1}}}
\end{aligned}
$$

In which variables in small letters are at the firm level and variables in capital letters at the aggregate level. Variables that are overlined with a bar denote averages. The subscripts S, E and X denote the group of surviving, entering and exiting firms. The subscripts i, j and t refer to firm, group and year. We refer to appendix C for a more detailed explanation and limit ourselves to how each line of equation (3) relates to the research questions. The first line of equation (3) is the *within* component of incumbent firms. According to classic macro-economic models of representative firms, this is the main source of aggregate productivity growth. In combination with the FHK model (see infra), the second line of equation (3) allows to quantify the contribution from job *reallocation* to aggregate productivity growth. Together the first two lines capture the total contribution from incumbent firms to aggregate productivity growth. The third and fifth line of equation (3) show whether the average productivity level of entering and exiting firms is higher or lower than the average productivity level of surviving firms. Based on theory, one would expect both the average productivity of new entrants and that of exiting firms to be lower than the average productivity of incumbents. Whether or not the magnitude of this difference changes over business cycles, depends on the discrepancies in behavior and demand each of these groups face over the business cycle. The fourth and sixth line of equation (3) learns whether job allocation is more efficient in entering or exiting firms than in incumbent firms. If we assume that firms learn about their productivity over their life cycle and hire labor according to their productivity levels, we expect both the components from lines four and six to be negative.

A potential drawback of this intuitive model is that the unit of observation is a firm in the economy instead of a firm in an industry in the economy. Thereby it does not take into account heterogeneity between industries. Since market shares are expressed in terms of labor units, this implies that for example financial institutions and metal producers hire labor from the same labor market. While this may be true to a certain extent, one could also argue that defining 'the market' at the economy-wide level is very rough. Since we estimate the production function at the NACE two-digit industry level, it is intuitive to define 'the market' as well at this level. This approach adds complexity to the model since job reallocation then must be assessed both within and between industries. For example, if high productive industries attract employment from low productive industries, this will result in an increase in aggregate productivity. The decomposition from the previous section is not able to capture this source of aggregate productivity growth. Therefore, MP propose an extension of their model that also includes an inter industry covariance component. To the best of our knowledge, we are the first to follow this approach apart from MP in their working paper. The extension of the model is as follows:

$$
\begin{aligned}
\Delta TFP = \quad & \underbrace{\sum_j ns_j(\overline{tfp}_{Sj2} - \overline{tfp}_{Sj1})}_{\Delta\overline{TFP}_{surv}} \\
& + \underbrace{\sum_j ns_j \left[\sum_i (ms_{iSj2} - \overline{ms}_{Sj2})(tfp_{iSj2} - \overline{tfp}_{Sj2}) - \sum_i (ms_{iSj1} - \overline{ms}_{Sj1})(tfp_{iSj1} - \overline{tfp}_{Sj1})\right]}_{\Delta \text{ Intra ind } Cov(TFP,MS)_{surv}} \\
& + \underbrace{\sum_j (ms_{Sj2} - ns_{Sj})(tfp_{Sj2} - tfp_{S2}) - \sum_j (ms_{Sj1} - ns_{Sj})(tfp_{Sj1} - tfp_{S1})}_{\Delta \text{ Inter ind } Cov(TFP,MS)_{surv}} \\
& + \underbrace{\sum_j ms_{j2} * ms_{Ej2}(tfp_{Ej2} - tfp_{Sj2})}_{\text{Intra ind}_{entr_t - surv_t}} \\
& + \underbrace{\sum_j ms_{j2} * ms_{Ej2}\left[(tfp_{Sj2} - tfp_{Ej2}) - (TFP_{S2} - TFP_{E2})\right]}_{\text{Inter ind}_{entr_t - surv_t}} \\
& + \underbrace{\sum_j ms_{j1} * ms_{Xj1}(tfp_{Sj1} - tfp_{Xj1})}_{\text{Intra ind}_{surv_{t-1} - exit_{t-1}}} \\
& + \underbrace{\sum_j ms_{j1} * ms_{Xj1}\left[(tfp_{Xj1} - tfp_{Sj1}) - (TFP_{X1} - TFP_{S1})\right]}_{\text{Inter ind}_{surv_{t-1} - exit_{t-1}}}
\end{aligned}
\tag{4}
$$

We again refer to appendix C for the complete derivation of the decomposition. The first two lines of equation (4) are identical to the first two lines of equation (3) except that they are calculated at the two-digit industry level and then aggregated up. The aggregation measure ns_j refers to market share expressed in number of firms. The first line again refers to the contribution to aggregate productivity growth that originates from *within* incumbent firms. The second line shows the contribution to aggregate productivity from job *(re)allocation within* industries. The third line learns whether there is employment growth in firms that operate in high productive industries. So it reflects job *(re)allocation between* industries.[6] The three first lines together show the contribution of incumbent firms to aggregate productivity growth. The fourth and fifth line relate to the contribution from

[6] The covariances regard simultaneous shifts in productivity and respectively intra-industry market share shifts and inter-industry market share shifts; hence they contain information on the efficiency of allocation, rather than solely reallocation.

entry and the sixth and seventh line to the contribution from exit to aggregate productivity growth. The fourth and sixth line are the intra-industry contributions from entry and exit. These are equal to the weighted average of industry aggregate productivity premia from entering and exiting firms over incumbent firms. The fifth and seventh line show the inter-industry contributions from entry and exit. These are obtained from the weighted sum of the differences in aggregate productivity premia of entering or exiting firms over incumbents at the industry and the aggregate level. Consider the following example: assume that aggregate productivity of incumbents is higher than aggregate productivity of entering and exiting firms and assume that these differences are not the same in all industries. Under this precondition, there is an additional channel through which aggregate productivity growth can arise, namely if there is more exit and less entry in those industries in which there is a higher discrepancy between aggregate productivity of incumbents on the one hand and entering and exiting firms on the other hand.

A drawback of decomposition models based on cross-sectional distributions is the inability to distinguish the evolution of market share (in our case, expressed in labor) from the evolution in productivity. The covariance components of two decompositions presented above learn whether job allocation is aligned with productivity. However, they do not distinguish between changes in market share and changes in productivity.[7] Hence, it is theoretically possible to find a positive impact of job reallocation even if market shares remain fixed, i.e. when the effect is solely driven by productivity changes. To rule out this confounding channel, we complement our analysis with a decomposition model that tracks firms over time instead of relying on cross-sectional distributions. More specifically, we use the FHK model to gain more insights in the role of job reallocation:

[7] The covariance changes can be due to simultaneous job reallocation and productivity reallocation. To see this more obviously, figure 3 shows scatter plots in which also the averages of productivity and jobs are shown. When firms move towards the 45 degree line, the covariance components will increase. This can happen both through changes in jobs and changes in productivity.

$$
\begin{aligned}
\Delta TFP = \quad & \underbrace{\sum_i ms_{Si1}(tfp_{Si2} - tfp_{Si1})}_{\Delta \text{Within}_{surv}} \\
& \underbrace{+\sum_i (ms_{Si2} - ms_{Si1})(tfp_{Si1} - tfp_1)}_{\Delta \text{Between}_{surv}} \\
& \underbrace{+\sum_i (ms_{Si2} - ms_{Si1})(tfp_{Si2} - tfp_{Si1})}_{\Delta \text{Covariance}_{surv}} \\
& \underbrace{+\sum_i ms_{Ei2}(tfp_{Ei2} - tfp_1)}_{\text{Entry}} \\
& \underbrace{-\sum_i ms_{Xi1}(tfp_{Xi1} - tfp_1)}_{\text{Exit}}
\end{aligned}
\tag{5}
$$

The first line in equation (5) refers to the contribution from *within* firm productivity growth. It fixes the market share in $t-1$ and aggregates up productivity growth in incumbent firms between $t-1$ and t. The second line is the *between* component. It fixes the deviation of an incumbent firm's productivity level compared to aggregate productivity in $t-1$ and regards the change in market share between $t-1$ and t. This component is particularly interesting with regard to the cleansing hypothesis because the MP decomposition regards simultaneous changes in productivity and market share while the between component captures solely the contribution to aggregate productivity from job reallocation. It is positive when jobs are reallocated to firms with high productivity. The cleansing hypothesis suggests this component to be positive, and particularly during or right after recession periods. The third line is usually labeled as the *covariance* component, although it is not a covariance from a mathematical perspective. The covariance component shows whether or not productivity evolves in the same direction as market share. The fifth and sixth line show the contribution from *entry* and *exit* to aggregate productivity growth. As discussed in MP, the reference levels for these components are imperfect. Therefore, these components will solely serve as robustness checks for our findings on entry and exit with the MP decompositions.

3 Data

3.1 Dataset

Our empirical analysis requires productivity measures for a representative sample of Belgian firms over a time span that includes both recession and non-recession periods. A dataset from the National Bank of Belgium is used to collect annual accounts for Belgium firms that were active in the period 1997-2014. From this database, we select all firms that are active in the private sector (NACE rev. 1.1 industry 1-74). All firms with limited liability are obliged to file their annual accounts. Small firms are allowed to report abbreviated annual accounts, while large firms are obliged to report full annual accounts.[8] Full annual accounts contain data that allow to calculate gross output production functions while data from abbreviated annual accounts restrict to value added production functions. Since only 7% of the firms files complete accounts, we rely on value added production functions such that the sample of firms is as representative as possible for the entire private sector of the Belgian economy. A detailed description of the selected variables from the annual accounts can be found in appendix B.3. We use deflators from the National Bank of Belgium and Eurostat to transform nominal values from annual accounts into real values. To define which years were crisis years for Belgium in our sample period, we use data from the National Bank of Belgium and a recession indicator from the OECD.[9] The textbook definition of a recession is two consecutive quarters of negative GDP growth. Figure 1 shows quarterly GDP growth for Belgium from 1996-2014. During this period, there are three recessions: Q1-2001 - Q4-2001; Q3-2008 - Q2-2009; Q2-2012 - Q1-2013. Obviously, the great recession of 2008-2009 was the most severe of the three. While GDP growth is the most frequently used indicator of recessions, there are other factors that signal recessions. We validate our identification of recession periods with the country specific composite leading indicators from the OECD, which include information on consumer confidence, production, demand, export

[8] A firm is defined as large when the average annual number of employees is higher than 100 or when at least two of the following thresholds are surpassed: (i) average annual number of employees equal to 50, (ii) turnover (excluding VAT) €7.300.000, (iii) balance sheet total €3.650.000.

[9] The OECD Composite Leading Indicators, "Composite Leading Indicators: Reference Turning Points and Component Series", www.oecd.org/std/cli (Accessed on 06/04/2016)

orders, employment and passenger car registrations. Based on such indicators, recession periods are defined as the period between one quarter after the peak and the trough of the composite leading indicator. Not surprisingly, we find the same three crisis periods in our sample based on these indicators, namely 2001, 2008-2009 and 2012.

A limitation of our data is one that is encountered in nearly all empirical work in the productivity literature, namely the absence of prices for inputs and outputs at the firm or product level. The inability to control for input and output price variation implies that it is impossible to distinguish between productivity and profitability. Productivity reflects physical efficiency while profitability depends not only on physical efficiency but also on prices, which reflect product differentiation and markups in addition to costs. The absence of data on prices requires to impose some assumptions on the market structure. More specifically, one has to assume single-product firms that produce a homogeneous product and are active in an industry that is characterized by perfectly competitive input and output markets. Only under these assumptions, our productivity measures would represent physical efficiency. Although it is common practice in the productivity literature to impose the aforementioned set of assumptions, it is rather implausible that firms produce a single good and are price takers in both the output and input market. De Loecker and Goldberg (2014) provide a comprehensive overview of the issues that come with estimating production functions and possible routes to overcome various biases. Unfortunately, the only way around imposing assumptions is to obtain output and input prices.[10] Since we do not have these, we proceed with the notion that we actually estimate sales generating production functions. Hence our productivity measures reflect residual profitability or more generally, firm performance, instead of purely true productivity.

As indicated in section 2, we use company accounts data for the estimation of production functions and the decompositions. Baily et al. (1992) already indicated in their seminal work on productivity decompositions that productivity decompositions are sensitive to outliers. This is not

[10]The pass-through literature however is flexible in output and input price variation. A representative paper in this literature is the one of Amiti et al. (2014). Unfortunately, this literature is based on a demand-based approach instead of a production function approach, which entails assumptions on demand, market structure and firm behavior. As we estimate productivity for a large cross section of industries, this is problematic.

surprising given the well established finding of large tails in productivity distributions and the importance of the first and second moments of the productivity distribution in productivity decompositions. Therefore, both the estimation of the production function and the decomposition presented in section 2 require data cleaning a priori. We refer to appendix B.3.5 for the choices we made regarding data cleaning, missing data and outliers. The most important restraints in terms of data originate from the use of loglinear transformations of our variables and the inability of the decompositions to cope with missing data. Therefore we are limited to a sample of firms for which none of the required variables is negative and for which productivity and market share measures can be obtained for each year they are active. After cleaning our data, we remain a sample of about 80.000 firms for the decompositions. Together, these firms represent 20% of the people working in the private sector and 11% of total value added created. Summary statistics are provided in table 1 below. Although necessary data cleaning reduced the sample size substantially, figure 2 shows that aggregate productivity growth based on our sample mimics well aggregate productivity growth calculated by the European commission, which indicates that our sample is indeed representative.

3.2 Measuring Productivity

The concept of total factor productivity (TFP) dates back to the work of Solow (1957), who defined rising TFP as rising output with constant capital and labor inputs. Although the research domain has developed substantially, the basic idea of TFP as residual output - after controlling for output created by labor and capital inputs - remains unchanged. There are numerous options available for economists to measure TFP.[11] The TFP estimates in this paper follow from semiparametric estimation of production functions. We refer to appendix B for a comprehensive overview of the estimation procedure. The prerequisite of having productivity measures for a sample as large as possible confines the choice of the estimation approach. Our data favors the use of value added production functions and investments to proxy for unobserved productivity. In appendix A we also present a robustness checks based on the more flexible translog production function. All production functions are estimated at the NACE two-digit industry level with the Wooldridge (2009) one-step estimator. Firm level TFP measures are indicated by tfp_{ijt} in which i refers to firm, j identifies the affiliation of a firm to an industry and t refers to year. The specification through which we obtain tfp_{ijt} is:

$$tfp_{ijt} = va_{ijt} - \hat{\beta}_{lj} * l_{ijt} - \hat{\beta}_{kj} * k_{ijt} \tag{6}$$

In which small letters indicate logarithmic transformations. va_{ijt} is deflated value added, l_{ijt} is the number of hours worked, k_{ijt} is deflated capital. $\hat{\beta}_{lj}$ and $\hat{\beta}_{kj}$ are the estimated production function coefficients of labor and capital. See table A10 in appendix B for an overview of the estimated production function coefficients per industry.

[11] For an extensive overview of various estimation techniques to obtain TFP measures, we refer to Van Biesebroeck (2007)

4 Results

4.1 Aggregate productivity growth

Before going into the effects of recent recessions on the micro origins of aggregate productivity growth, we discuss some general findings about aggregate productivity growth, incumbents, entering and exiting firms based on the averages from table 2. Over the sample period 1997-2014, yearly productivity growth in the entire private sector is on average 0.90% with a standard deviation of 1.31%. Altogether, incumbent firms almost entirely determine the aggregate productivity evolution since the contributions to the aggregate from entry and exit offset each other.[12] This is in line with expectations since the Belgian economy is an advanced and relatively stable economy. For the group incumbent firms, we find large volatility in average productivity over time. Average productivity is procyclical, which is in line with the literature. According to Basu and Fernald (2001), this can be explained by procyclical technology, capacity utilization or by imperfect competition and increasing returns. Job reallocation consistently positively contributes to aggregate productivity growth. This source of aggregate productivity growth is less volatile than within firm productivity growth. Consequently, fluctuations in aggregate productivity over the business cycle are largely driven by productivity shocks within incumbent firms. Average productivity is consistently lower in the cross section of exiting firms and therefore exit contributes positively to aggregate productivity growth. More precisely, this effect increases productivity on average by 0.85% points, with a standard deviation of 0.27%. Job allocation is more aligned with TFP in exiting firms than in incumbent firms (see Table 10), which induces a negative contribution to productivity growth of -0.38% on average with a standard deviation of 0.35%. After the contributions from incumbent and exiting firms, the remainder of aggregate productivity growth is explained by the dynamics in the group of entering firms. Entering firms are on average less productive than incumbent firms. As a result, entry

[12] In our decompositions, entering firms are firms that are active for one year or less. As discussed in section 4.3, this explains why it seems like they do not contribute to aggregate productivity growth. In fact, the contribution from young firms (older than one year) to aggregated productivity will be absorbed into the components of incumbent firms. The yearly entry and exit rates in our sample of firms for the decompositions is respectively 5-8% and 3-5% which is lower than reported in Geurts (2015). This is due to necessary data cleaning to apply the decomposition. We are aware of the potential consequences of data cleaning and discuss this in appendix B.3.5.

initially has a negative impact on aggregate productivity of -0.27% on average and the standard deviation of this effect is 0.07%. The alignment between TFP and jobs is lowest in the cross section of entering firms (see table 10). This induces an additional negative contribution from firm entry to aggregate productivity growth of 0.17% on average with a standard deviation of 0.07%.

4.2 Cleansing effects of recessions

Economy-wide decomposition

The main question we want to answer in our empirical analysis is whether or not recent recessions displayed a cleansing effect, i.e. did recession periods cause job reallocation from low productive towards high productive firms? As discussed in section 2, we verify this hypothesis by regarding the $\Delta Cov(TFP, MS)_{surv}$ component from the MP decomposition and the $\Delta \text{Between}_{surv}$ component from the FHK decomposition. The MP decomposition shows how much of productivity growth is explained by changes in the alignment between jobs and productivity while the FHK decomposition allows to distinguish between job reallocation and productivity shocks. In recessions periods, $\Delta Cov(TFP, MS)_{surv}$ is on average 1.42% while in non-recession periods it is only 0.70% on average (see table 2 and figure 6). So in recession periods, the contribution from reallocation to aggregate productivity growth is double as high as in non-recession periods. This also follows from the $\Delta \text{Between}_{surv}$ component, which is 0.79% on average in recession periods and 0.38% on average in non-recession periods (see table 3 and figure 8).[13] These results support the hypothesis that recent recessions did indeed induce cleansing effects.

Our finding that the great recession induced a cleansing effect in Belgium is not consistent the conclusion of Foster et al. (2015), who found for the US that the great recession was less productivity enhancing than earlier recessions. A potential explanation for the difference between our results and theirs, is the way jobs are measured. Foster et al. (2015) measure jobs in full

[13]Note that the MP decomposition shows productivity growth from simultaneous changes in productivity and jobs while the FHK decomposition shows productivity growth from job reallocation only. This explains why the $\Delta Cov(TFP, MS)_{surv}$ component is larger than the $\Delta \text{Between}_{surv}$ component.

time equivalents while we measure jobs in hours worked.[14] Figures 4 and 5 show that gross job reallocation, measured as in Davis and Haltiwanger (1992), is indeed lower during the great recession when measured in full time equivalents. This is because, unlike when jobs are measured in hours worked, there is no strong increase in job destruction when jobs are measured in full time equivalents. This could be a consequence of firms doing labor hoarding during recession periods, i.e. firms did not lay off employees when they would otherwise do so, thereby guaranteeing that talent will be available to the firm when economic conditions improve. This was simplified for Belgian firms during the great recession as the government allowed firms to temporarily make people unemployed and gave financial support to those employees.[15] Tables A5 and A6 show the results of the MP and FHK decompositions in which jobs are measured in full time equivalents. Comparing the average contributions of reallocation to productivity growth based on these results, we find that the $\Delta Cov(TFP, MS)_{surv}$ component is on average 1.18% in recession periods and 0.82% on average in non-recession periods while the $\Delta \text{Between}_{surv}$ component is 0.45% on average in recession periods and 0.42% on average in non-recession periods. What stands out in the results, is that the high covariance and between component in the great recession do not show up in the decompositions that use jobs expressed in full time equivalents. As a result, we come to a similar conclusion as Foster et al. (2015) when expressing jobs as full time equivalents instead of in hours worked, namely that the great recession was associated with productivity enhancing job reallocation that was larger than in non-recession periods, but this cleansing effect was less outspoken than in other recession periods.

In the remainder of this section, we disentangle our findings at the industry level, highlight other findings related to the cleansing effect and present some robustness checks.

[14] Foster et al. (2015) uses job creation and job destruction measures from the U.S. Business Dynamics Statistics, in which employment is defined as *'Paid employment of full and part-time employees, including salaried officers and executives of corporations, who were on the payroll in the pay period including March 12. Included are employees on sick leave, holidays, and vacations; not included are proprietors and partners of unincorporated businesses.'* This is consistent with the Belgian definition of a full time equivalent. See section B.3.2 in appendix for further information on the job measures we use.

[15] Temporary unemployment support already exists for a long time, but only since the great recession it also applies to white collar workers.

Industry Decomposition

The extended MP model allows to obtain further insights in job reallocation by providing a measure of both within and between industry job reallocation.[16] Table 4 shows that productivity increasing reallocation takes place both within (Δ Intra ind $Cov(TFP, MS)_{surv}$) and between (Δ Inter ind $Cov(TFP, MS)_{surv}$) industries, and the magnitude of this effect is for most years larger within industries than between industries. This is also the case in the first year of the great recession. In 2009 however, the contribution from reallocation to aggregate productivity is driven by between industry reallocation. To gain deeper understanding in this anomaly, we compare the industry decomposition based on hours worked (table 4) with the industry decomposition based on full time equivalents (table A9) for the great recession. The contribution from within industry reallocation is similar in both decompositions, but in 2009 the contribution from between industry reallocation is only 0.50% when jobs are measured in full time equivalents while it is 1.25% when jobs are measured in hours worked. The reason for this is that in low productive industries, there was a substantial drop in the number of hours worked but the number of full time equivalents did not drop to the same extent, indicating that labor hoarding was especially applied in low productive industries.

Furthermore, it is interesting to look at the evolution of the intra and inter industry covariances. Figure 12 shows how these covariances evolve over time. An interesting finding is that both increase over time, so high productive firms become more successful in attracting employees, thereby increasing aggregate productivity. The intra industry covariance amounts to 25% for the private sector. In an accounting sense, this implies that aggregate productivity is 25% higher than when jobs would be randomly allocated within industries. Bartelsman et al. (2013) find this covariance to be 50% for US manufacturing industries, but only 20-30% in Western Europe, so our results are in line with their findings.

[16] As mentioned before and more explicitly shown for both the general and the extended MP decomposition in appendix C and figure 3, covariances do not distinguish between aggregate effects from job reallocation and aggregate effects from productivity shocks. Therefore, findings based on these decompositions should rather be interpreted as findings on the alignment between productivity and market share expressed in jobs.

Other findings

So far, we discussed how recession periods induced productivity enhancing reallocation. However, this does not imply that a social planner wants recessions to take place. Our decompositions show that recession periods also have negative effects on productivity growth in incumbent firms. Average productivity in incumbent firms is clearly lower during recession periods, with negative consequences for aggregate productivity growth. The literature on cleansing effects also proposed alternative mechanisms that counteract the cleansing effect. The positive consequences in the short run from cleansing effects of recessions could be mitigated or offset by negative consequences from a scarring effect of recessions in the long run. The scarring effect states that the recession kills potential good entrants in their infancy. When young firms with high potential are unable to survive, this negatively impacts aggregate productivity in the long run (Ouyang, 2009). Indeed, we see that it is harder for young firms to survive in crisis periods, for example in the great recession and the 2012 recession respectively 55% and 50% of the exiting firms is less than five years old, while on average only 33% of exiting firms is less than five years old. This suggests the great recession did have a scarring effect in Belgium.

Robustness checks

We test the robustness of our findings by performing the decompositions based on TFP estimates from Translog production functions and by using labor productivity instead of TFP (see section A in appendix). The results of the decompositions based on TFP measures from Translog production functions are in line with the findings from TFP measures obtained from the standard Cobb Douglas production function. In fact, the cleansing effect is more outspoken using TFP measures from Translog production functions. When using labor productivity instead of TFP, we find that aggregate productivity growth originating from reallocation ($\Delta Cov(LP, MS)_{surv}$) decreases over time, but goes up in recession periods, which is consistent with our findings based on TFP measures.

4.3 Entry and exit

Entry of high productive firms and exit of obsolete firms are important drivers of aggregate productivity growth (Clementi and Palazzo, 2016). We question the effects of recent recessions on these determinants of aggregate productivity growth. To this aim, we rely on the MP decomposition because it is superior to other methods for measuring productivity growth from entry and exit (see section 2 and appendix C).[17] The averages of columns five to eight of table 2 learn that entering and exiting firms are on average less productive than incumbent firms and that the link between market share and productivity is strongest in exiting firms and weakest in entering firms (also see table 10). Exit of low productive firms consistently contributes to productivity growth. However, the opposite is true for entering firms. One may be intended to conclude from these results that new firms do not contribute to aggregate productivity growth. Nonetheless, the literature provides various explanations for the initially negative impact of entering firms on aggregate productivity growth. As documented by Aw et al. (2001), entrants are a heterogeneous group. Some of them fail, but others grow and are important for aggregate productivity growth in the long run (Hyytinen and Maliranta, 2013). Also entrants could charge low prices to gain market share (Foster et al., 2008). Since we estimate sales generating production functions, we are unable to correct for this potential bias. Moreover, entering firms possibly still have to optimize their production processes and learn about their own potential and the market. This will show up in lower productivity and will distort the relation between market share and productivity in the cross section of entering firms. The opposite is true for exiting firms. These firms have already learned about their productivity and market potential, and therefore the number of employees will be more aligned with productivity in this group of firms, which shows up in higher covariance components for exiting firms.

The difference in average productivity between incumbent, entering and exiting firms seems not to be substantially affected by recessions. It stands out that over time the difference between

[17] Also, the entry and exit components from the MP decomposition provide richer insights than these of the FHK decomposition, which is why these only serve as robustness check. As expected, the sum of the two entry and two exit components from the MP decomposition are always close to the entry and exit components reported in the FHK decomposition.

average productivity in incumbent and exiting firms declined. The narrowing of this gap squares with the idea that the Belgian economy became more competitive. Furthermore it is interesting to relate the evolution in $\Delta\overline{TFP}_{surv}$ with the $\overline{TFP}_{entr_t-surv_t}$ and $\overline{TFP}_{surv_{t-1}-exit_{t-1}}$ components. In all recession periods, average productivity in incumbent firms goes down. Since the differences in average productivity with entering and exiting firms does not substantially differ between recession and non-recession periods, this shows that entering and exiting firms faced similar productivity shocks from recessions as incumbent firms.[18]

By comparing the covariances between market share and productivity for the group of surviving, entering and exiting firms, we learn about the type of firms that enter and exit. Table 2 shows that the $Cov(TFP, MS)_{surv_{t-1}-exit_{t-1}}$ component was particularly large in 2003 and 2010, meaning that the difference in the covariances between incumbent and exiting firms was large. Table 10 shows that this is due to a high covariance between market share and productivity in the cross section of exiting firms in 2002 and 2009, which are both at the end of recession periods. So in these years, more exiting firms can be found in the first and third quadrant of figure 3, meaning that at the end of recessions there are more large firms with high productivity and small firms with low productivity that exit, resulting in lower aggregate productivity. Also in the group of entering firms, there seems to be an effect from recession periods on the covariance component. Table 2 shows that $Cov(TFP, MS)_{entr_t-surv_t}$ is lower in recession periods. From table 10 we learn this is the result of a low covariance between market share and productivity in the group of entering firms during recession periods. So during recessions, the link between productivity and employment is less strong. This is consistent with the scarring effect of recessions hypothesis, namely that recessions distort growth opportunities of high potential entrants.

The extended industry to aggregate MP decomposition has a different approach to infer the aggregate impact of entry and exit (see section 2 and appendix C). The $Intra\,ind_{entr_t-surv_t}$ and $Intra\,ind_{surv_{t-1}-exit_{t-1}}$ components from table 4 show that industry aggregate TFP of entering and

[18]Note that this result is also a consequence of the number of exiting firms that did not go up substantially in the great recession. This finding emerges in our sample, but also in the business demography statistics for Belgium on Eurostat, which show that only after the great recession the number of firm deaths increased.

exiting firms is generally lower than industry aggregate TFP of incumbent firms, which is consistent with our previous findings. One exception is the year 2010. This indicates that in the aftermath of the great recession there was a large share of industries in which industry aggregate TFP of exiting firms was higher than that of incumbent firms.[19] Furthermore, the $Inter\,ind_{entr_t-surv_t}$ component from table 4 shows that firms consistently enter more in industries in which entrants perform better. More specifically, since in most industries entering firms have lower aggregate productivity, this means that there is more firm entry, expressed in number of jobs, in industries where productivity of entrants is closer to productivity of incumbents. Finally, the $Inter\,ind_{surv_{t-1}-exit_{t-1}}$ component from table 4 is mostly negative, although positive for the years 2002 and 2010, both after recession periods. This indicates that in the aftermath of recessions the loss of jobs from firm exit is larger in industries in which exiting firms have productivity levels that are relatively close to those of incumbent firms.

4.4 Manufacturing vs. Services

Tables (5) to (8) provide deeper insights in how the manufacturing sector compares with the services sector. This is particularly interesting because, like in most European countries, since long there is a shift in employment from the manufacturing to the services sector. Applying our empirical framework separately to the manufacturing and services sector allows us to contribute to the discussion on how a shift towards a services economy affects economic growth and how recessions affect these sectors differently. When comparing aggregate productivity growth in the manufacturing with the services sector, it shows that productivity growth is on average only 0.30% per year in the services sector while it is 1.54% in the manufacturing sector. One immediate and clear finding is that within firm productivity growth is positive on average in the manufacturing sector while it is negative on average in the services sector, see third column of tables (5) and (7). This is in line with the premise that it is harder to realize productivity growth in services activities by nature.

[19] Note that this was not apparent from the economy-wide MP decomposition, which showed that unweighted average productivity of incumbent firms was larger than unweighted average productivity of exiting firms.

Looking at the average contributions from incumbent, entering and exiting firms to aggregate productivity, we find that in the manufacturing sector, productivity growth is largely driven by incumbent firms while in the services sector productivity growth is largely driven by industry dynamics from entry and exit. Both in the manufacturing and services sector it is generally the case that entering and exiting firms have lower productivity than incumbents while job allocation is most efficient in the group of exiting firms and least efficient in the group of entering firms. However, this pattern is far more pronounced in the services sector.

Furthermore, the $\overline{TFP}_{surv_{t-1}-exit_{t-1}}$ component of table (7) shows that the discrepancy in average productivity between exiting and incumbent firms in the services sector is relatively large in the great recession.[20] From the $Cov(TFP, MS)_{surv_{t-1}-exit_{t-1}}$ component we learn that there is more exit of firms for which their size is representative of their productivity at the end of the great recession.

On the discussion about cleansing effects from recessions, we find strong evidence of cleansing effects in the manufacturing sector but the same cannot be said for the services sector. Figure 13 shows the evolution of the difference in the covariance component of the MP decomposition, i.e. $\Delta Cov(TFP, MS)_{surv,manufacturing} - \Delta Cov(TFP, MS)_{surv,services}$ from tables 5 and 7, and the difference in the between component of the FHK decomposition, i.e. $\Delta Between_{surv,manufacturing} - \Delta Between_{surv,services}$ from tables 6 and 8. These differences are positive in recession periods, especially in the great recession, indicating stronger cleansing in manufacturing than in services industries. Especially in 2009, which is the deepest recession year of sample period (see figure 1), there is a 3.97% aggregate productivity growth in the manufacturing sector due to increased efficiency of job allocation, while the average contribution of this component to aggregate productivity is only 0.82%. The between component from the FHK decomposition is also far above average in 2009, which confirms that job reallocation rather than changes in productivity did induce productivity growth in the manufacturing sector.

[20] In principle, this result could also originate from a higher market share of exiting firms in these periods, however this is not the case for our sample of firms.

So altogether, we find proof of cleansing effects from recessions in the manufacturing sector. For the services sector, the between components from the FHK decomposition are slightly higher than average during or right after recession periods, which indicates there is job reallocation towards firms that have higher than average productivity. However, the strong negative covariance terms from the FHK decomposition indicate that downsizing firms become more productive and upsizing firms less productive. This also follows from absence of clear patterns in the MP decomposition. So in the services sector, the modestly positive effect from cleansing is confounded by lower productivity for these upsizing firms in the subsequent year.

5 Conclusions

This paper contributes to the literature by investigating how recessions affect the micro origins of aggregate productivity growth. To this end, we use firm level data from the entire private sector of Belgium for the years $1997-2014$ and apply the recent decomposition model of Melitz and Polanec (2015) and the Foster et al. (2001) decomposition model. The empirical framework is very rich and offers a wide variety of insights on the determinants of aggregate productivity growth in incumbent, entering and exiting firms over the business cycle.

In this paper we answer three questions. The first and foremost question we answer is whether recent recessions had a cleansing effect, i.e. was productivity growth from job reallocation higher in recession periods than in non-recession periods? By using jobs as aggregation measure for firm level productivity, the reallocation components in the decompositions reflect the contribution to aggregate productivity from job reallocation. We find that aggregate productivity growth from reallocation is consistently positive over time. This is in line with earlier work on the Belgian private sector (Van Beveren and Vanormelingen, 2014). The contribution of within firm productivity growth on the other hand has a procyclical nature. Hence, aggregate productivity variation over the business cycle is largely driven by productivity shocks within incumbent firms. The contribution to aggregate productivity from job reallocation is substantially larger during and right after recession periods than in non-recession periods. Hence, we conclude that recessions displayed a cleansing effect, i.e. recessions induced job reallocation towards more productive firms. This cleansing effect takes place both within and between industries, although it is more prominent within industries. However, our findings depend on how jobs are measured. When measuring jobs based on full time equivalents instead of hours worked as in Foster et al. (2015), we reach a similar conclusion for Belgium as was found for the US, namely that the great recession was associated with productivity enhancing job reallocation that was larger than in non-recession periods, but this cleansing effect was less outspoken than in other recession periods. The reason why we do find cleansing effects when measuring jobs in hours worked, could be that firms did labor hoarding in the great recession.

The second question we answer is how entering and exiting firms compare to incumbent firms in recession versus non-recession periods. Overall, incumbent firms are the most important source of aggregate productivity growth, while the role of entry and exit is rather moderate. Average productivity in entering and exiting firms is lower than in incumbent firms, and the alignment between jobs and productivity is strongest in exiting firms and weakest in entering firms. Entering and exiting firms seem to face similar productivity shocks from recessions. However, the covariance between market share and productivity is higher for exiting firms at the end of recession periods. The reason for this is that, at the end of recessions, there is more exit of firms for which their size is representative of their productivity. Furthermore, we find some indications that recessions induce a scarring effect on entrants, i.e. recessions restrain entrants from growing.

The last question we answer is to which extent manufacturing and services industries differ in realizing productivity growth over the business cycle. As indicated by Foster et al. (2015), the literature so far did not provide an answer on how the cleansing effect differs between manufacturing and services industries. We find strong evidence for cleansing effects from recessions in the manufacturing sector, but the same cannot be said for the services sector. Instead, we find that exit of low productive firms is an important determinant of aggregate productivity growth in services industries. The same is not true for manufacturing industries, in which productivity dynamics in incumbent firms largely determine aggregate productivity.

A limitation of papers based on productivity decompositions is the absence of confidence intervals, and thus the degree of uncertainty on the results they provide. This limits the insights one can obtain from them to stylized facts. One way forward could be to construct confidence intervals based on bootstrapping. Another way forward would be to extend the model of Hyytinen et al. (2016), who show how a moment-based estimation procedure can be used to compute standard errors for the static Olley and Pakes (1996) decomposition, to the more advanced Melitz and Polanec (2015) model. Furthermore, it would be interesting to investigate which firm level heterogeneity drives the reallocation components.

References

D. A. Ackerberg, K. Caves, and G. Frazer. Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451, 2015.

P. Aghion and G. Saint-Paul. On the virtue of bad times: An analysis of the interaction between economic fluctuations and productivity growth. *CEPR Discussion Paper 578*, 1991.

M. Amiti, O. Itshkhoki, and J. Konings. Importers, exporters and exchange rate disconnect. *American Economic Review*, 104(7):1942–1978, 2014.

B. Y. Aw, X. Chen, and M. J. Roberts. Firm-level evidence on productivity differentials and turnover in taiwanese manufacturing. *Journal of Development Economics*, 66:51–86, 2001.

M. N. Baily, C. Hulten, and D. Campbell. Productivity dynamics in manufacturing plants. *Brookings Papers on Economic Activity: Microeconomics*, pages 187–267, 1992.

M. N. Baily, E. J. Bartelsman, and J. Haltiwanger. Labor productivity: Structural change and cyclical dynamics. *The Review of Economics and Statistics*, 83(7):420–433, 2001.

A. Banerjee and B. Moll. Why does misallocation persist? *American Economic Journal: Macroeconomics*, 2(1):189–206, 2010.

G. Barlevy. The sullying effect of recessions. *The Review of Economic Studies*, 69(1):65–96, 2002.

E. Bartelsman, J. Haltiwanger, and S. Scarpetta. Microeconomic evidence of creative destruction in industrial and developing countries. *IZA Discussion Paper Series*, 2004.

E. Bartelsman, J. Haltiwanger, and S. Scarpetta. Cross-country differences in productivity: The role of allocation and selection. *American Economic Review*, pages 305–334, 2013.

S. Basu and J. G. Fernald. *Why Is Productivity Procyclical? Why Do We Care?* Chicago: University of Chicago Press, 2001.

S. Basu and J. G. Fernald. Aggregate productivity and aggregate technology. *European Economic Review*, 46(6):963–991, 2002.

S. Bond and M. Söderbom. Adjustment costs and the identification of cobb douglas production functions. *Working Paper Series No. 05/04 The Institute for Fiscal Studies*, 2005.

R. J. Caballero and M. L. Hammour. The cleansing effect of recessions. *The American Economic Review*, 84(5):1350–1368, 1994.

F. Caselli. *Accounting for Cross-Country Income Differences, Handbook of Economic Growth*, volume 1A. Amsterdam: Elsevier, 2005.

L. G. Clementi and B. Palazzo. Entry, exit, firm dynamics, and aggregate fluctuations. *American Economic Journal: Macroeconomics*, 8(3):1–41, 2016.

A. Collard-Wexler, J. Asker, and J. De Loecker. *Productivity Volatility and the Misallocation of Resources in Developing Economies*. NBER working paper 17175, 2011.

S. J. Davis and J. Haltiwanger. Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, 107(3):819–863, 1992.

J. De Loecker and P. K. Goldberg. Firm performance in a global market. *The Annual Review of Economics*, 6:201–227, 2014.

E. D. Domar. On the measurement of technological change. *The Economic Journal*, 71(284): 709–729, 1961.

S. Dowrick and D.-T. Nguyen. Oecd comparative economic growth 1950-85: Catch-up and convergence. *The American Economic Review*, 79(5):1010–1030, 1989.

W. Easterly and R. Levine. It's not factor accumulation: Stylized facts and growth models. *The World Bank Economic Review*, 15(2):177–219, 2001.

L. Foster, J. Haltiwanger, and C. Krizan. *Aggregate Productivity Growth: Lessons from Microeconomic Evidence*. Chicago: University of Chicago Press, 2001.

L. Foster, J. Haltiwanger, and C. Syverson. Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1):394–425, 2008.

L. Foster, C. Grim, and J. Haltiwanger. Reallocation in the great recession: Cleansing or not? *Journal of Labor Economics*, 34(1):293–331, 2015.

A. Gandhi, S. Navarro, and D. Rivers. On the identification of production functions: How heterogeneous is productivity. Journal of Political Economy, forthcoming.

K. Geurts. How sensitive are measures of firm and employment dynamics to longitudinal linkage problems. *Discussion paper series 15.10, Center for Economic Studies, KU Leuven*, 2015.

R. J. Gordon. *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton University Press, 2016.

Z. Griliches and H. Regev. Firm productivity in israeli industry 1979-1988. *Journal of Econometrics*, 65(1):175–203, 1995.

R. E. Hall and C. I. Jones. Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*, 114(1):83–116, 1999.

M. J. Harper. Estimating capital inputs for productivity measurement: An overview of u.s. concepts and methods. *International Statistical Review*, 67(3):327–337, 1999.

H. A. Hopenhayn. Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, 60(5): 1127–1150, 1992.

C. R. Hulten. Growth accounting with intermediate inputs. *The Review of Economic Studies*, 45 (3):511–518, 1978.

A. Hyytinen and M. Maliranta. Firm lifecycles and evolution of industry productivity. *Research Policy*, 42(5):1080–1098, 2013.

A. Hyytinen, P. Ilmakunnas, and M. Maliranta. Olley-pakes productivity decomposition: Computation and inference. *Journal of the Royal Statistical Society A*, 179(3):749–761, 2016.

C. I. Jones and P. M. Romer. The new kaldor facts: Ideas, institutions, population, and human capital. *American Economic Journal: Macroeconomics*, 2(1):224–245, 2010.

J. Konings. Job creation and job destruction in the uk manufacturing sector. *Oxford Bulletin of Economics and Statistics*, 57(1), 1995.

P. R. Krugman. *The Age of Diminished Expectations.* Cambridge: MIT Press, 1994.

J. Levinsohn and A. Petrin. Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2):317–341, 2003.

J. Marschak and W. H. Andrews. Random simultaneous equations and the theory of production. *Econometrica*, 12(3):143–205, 1944.

M. J. Melitz and S. Polanec. Dynamic olley-pakes productivity decomposition with entry and exit. *RAND Journal of Economics*, 46(2):362–375, 2015.

N. Mitsukuni, A. Petrin, and S. Polanec. Exploring reallocation's apparent weak contribution to growth. *Journal of Productivity Analysis*, 42(2):187–210, 2014.

G. S. Olley and A. Pakes. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297, 1996.

M. Ouyang. The scarring effect of recessions. *Journal of Monetary Economics*, 56(2):184–199, 2009.

C. Pages, G. Pierre, and S. Scarpetta. *Job Creation in Latin America and the Caribbean.* Recent Trends and Policy Challenges, 2009.

A. Petrin and J. Levinsohn. Measuring aggregate productivity growth using plant -level data. *RAND Journal of Economics*, 43(4):705–725, 2012.

D. Restuccia and R. Rogerson. Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11:707–720, 2008.

J. A. Schumpeter. Business cycles. *New York: McGraw-Hill*, 1939.

R. Solow. Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3):312–320, 1957.

C. Syverson. Product substitutability and productivity dispersion. *Review of Economics and Statistics*, 86(2):534–550, 2004.

I. Van Beveren and S. Vanormelingen. Human capital, firm capabilities and productivity growth. *National Bank of Belgium Working Paper 257*, 2014.

J. Van Biesebroeck. Robustness of productivity estimates. *The Journal of Industrial Economics*, 55(3):529–569, 2007.

J. Van Biesebroeck. Aggregating and decomposing productivity. *Review of Business and Economics*, 53(2):122–146, 2008.

J. Wooldridge. On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, 104(3):112–114, 2009.

6 Tables

6.1 Summary statistics

Table 1: Summary Statistics

Variable	Mean	Median	Std. Deviation	Minimum	Maximum
Employees (FTE)	8.91	3.30	40.96	0.00	4347.00
Hours Worked	13943.67	5200.00	62027.85	2.00	6.64e+06
Value Added	608640.02	185329.18	5.51e+06	180.81	1.40e+09
Ln TFP	4.96	4.88	0.73	0.01	10.17
Capital	590252.42	102690.20	5.45e+06	1.15	5.58e+08

Notes: Summary statistics for the sample of 80.000 firms from the Belgian private sector that can be used for the productivity decompositions.

6.2 Decomposition for entire private sector

Table 2: MP decomposition - NACE 1-74

Year	△ TFP	Surviving firms		Entering firms		Exiting firms	
		△ $\overline{TFP}_{surv}$	△ Cov(TFP,MS)$_{surv}$	$\overline{TFP}_{entr_t-surv_t}$	Cov(TFP,MS)$_{entry_t-surv_t}$	$\overline{TFP}_{surv_{t-1}-exit_{t-1}}$	Cov(TFP,MS)$_{surv_{t-1}-exit_{t-1}}$
1998	-0.18	-1.73	1.57	-0.36	-0.12	1.06	-0.61
1999	2.15	0.86	0.91	-0.35	-0.06	0.93	-0.14
2000	1.72	0.40	0.98	-0.29	-0.09	1.15	-0.42
2001	1.95	-0.78	2.52	-0.26	-0.18	1.29	-0.63
2002	1.19	-0.18	1.17	-0.24	-0.25	1.33	-0.63
2003	1.77	0.56	1.43	-0.14	-0.14	1.13	-1.08
2004	1.70	-0.11	1.26	-0.16	-0.12	1.01	-0.18
2005	0.79	0.33	0.38	-0.21	-0.15	0.70	-0.25
2006	1.78	1.56	-0.22	-0.24	-0.11	0.74	0.05
2007	1.29	1.80	-0.39	-0.22	-0.25	0.60	-0.24
2008	-1.78	-1.98	0.33	-0.26	-0.27	0.71	-0.30
2009	2.40	0.95	1.56	-0.31	-0.23	0.68	-0.24
2010	-0.24	0.68	-0.05	-0.29	-0.26	0.89	-1.21
2011	-1.44	-0.67	-0.62	-0.36	-0.17	0.53	-0.15
2012	-0.94	-2.06	1.25	-0.31	-0.21	0.58	-0.17
2013	1.34	0.54	0.66	-0.19	-0.18	0.50	0.00
2014	1.83	-0.19	2.06	-0.32	-0.08	0.65	-0.29
Total	0.90(1.31)	-0.00(1.14)	0.87(0.87)	-0.27(0.07)	-0.17(0.07)	0.85(0.27)	-0.38(0.35)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

Table 3: FHK decomposition - NACE 1-74

Year	△ TFP	Surviving firms			Entry	Exit
		△ Within$_{surv}$	△ Between$_{surv}$	△ Covariance$_{surv}$		
1998	-0.18	0.25	0.27	-0.66	-0.47	0.43
1999	2.15	1.88	0.32	-0.44	-0.37	0.76
2000	1.72	1.48	0.42	-0.53	-0.34	0.69
2001	1.95	1.53	0.63	-0.42	-0.41	0.63
2002	1.19	0.79	0.74	-0.54	-0.47	0.67
2003	1.77	1.77	0.65	-0.46	-0.24	0.04
2004	1.70	1.37	0.22	-0.44	-0.25	0.80
2005	0.79	0.62	0.54	-0.47	-0.34	0.43
2006	1.78	1.80	0.06	-0.54	-0.31	0.77
2007	1.29	1.90	0.00	-0.52	-0.44	0.35
2008	-1.78	-1.42	0.26	-0.46	-0.56	0.40
2009	2.40	1.51	1.34	-0.39	-0.49	0.43
2010	-0.24	0.91	0.19	-0.49	-0.55	-0.31
2011	-1.44	-0.74	0.05	-0.58	-0.55	0.38
2012	-0.94	-1.14	0.91	-0.57	-0.53	0.40
2013	1.34	0.85	0.93	-0.59	-0.34	0.49
2014	1.83	1.96	0.48	-0.61	-0.35	0.35
Total	0.90(1.31)	0.90(1.08)	0.47(0.36)	-0.51(0.07)	-0.41(0.11)	0.45(0.28)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

6.3 Extended Decomposition

Table 4: MP industry to sector decomposition - NACE 1-74

Year	△ TFP	Surviving firms			Entering firms		Exiting firms	
		△ $\overline{TFP}_{surv}$	△ Intra Ind Cov(TFP,MS)$_{surv}$	△ Inter ind Cov(TFP,MS)$_{surv}$	Intra Ind$_{entr_t-surv_t}$	Inter Ind$_{entr_t-surv_t}$	Intra Ind$_{surv_{t-1}-exit_{t-1}}$	Inter Ind$_{surv_{t-1}-exit_{t-1}}$
1998	-0.18	-1.73	0.90	0.67	-0.69	0.21	0.70	-0.25
1999	2.15	0.86	0.51	0.40	-0.57	0.16	0.70	0.08
2000	1.72	0.40	0.47	0.50	-0.52	0.15	0.87	-0.15
2001	1.95	-0.78	1.54	0.99	-0.53	0.08	0.60	0.06
2002	1.19	-0.18	0.84	0.33	-0.60	0.10	0.55	0.14
2003	1.77	0.56	0.25	1.18	-0.54	0.26	0.41	-0.36
2004	1.70	-0.11	0.52	0.74	-0.52	0.24	0.49	0.33
2005	0.79	0.33	0.28	0.10	-0.61	0.25	0.37	0.08
2006	1.78	1.56	0.19	-0.41	-0.61	0.26	0.58	0.20
2007	1.29	1.80	0.23	-0.62	-0.65	0.18	0.41	-0.05
2008	-1.78	-1.98	1.04	-0.71	-0.73	0.19	0.45	-0.04
2009	2.40	0.95	0.31	1.25	-0.77	0.23	0.50	-0.06
2010	-0.24	0.68	-0.06	0.01	-0.74	0.19	-0.46	0.14
2011	-1.44	-0.67	0.16	-0.78	-0.77	0.23	0.50	-0.12
2012	-0.94	-2.06	0.88	0.36	-0.73	0.20	0.46	-0.05
2013	1.34	0.54	0.39	0.28	-0.57	0.20	0.56	-0.06
2014	1.83	-0.19	1.43	0.63	-0.74	0.35	0.52	-0.16
Total	0.90(1.31)	-0.00(1.14)	0.58(0.45)	0.29(0.63)	-0.64(0.09)	0.20(0.06)	0.48(0.27)	-0.02(0.17)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

6.4 Decomposition for manufacturing sector

Table 5: MP decomposition - Manufacturing sector - NACE 15-36

Year	△ TFP	Surviving firms		Entering firms		Exiting firms	
		△ $\overline{TFP}_{surv}$	△ Cov(TFP,MS)$_{surv}$	$\overline{TFP}_{entr_t-surv_t}$	Cov(TFP,MS)$_{entry_t-surv_t}$	$\overline{TFP}_{surv_{t-1}-exit_{t-1}}$	Cov(TFP,MS)$_{surv_{t-1}-exit_{t-1}}$
1998	2.32	2.27	0.12	-0.15	-0.16	0.82	-0.58
1999	2.98	0.08	1.99	-0.11	0.09	0.58	0.36
2000	2.17	3.27	-1.44	-0.11	-0.07	0.83	-0.31
2001	2.87	0.65	1.83	-0.06	-0.14	1.08	-0.49
2002	1.26	-0.53	1.68	-0.07	-0.29	0.91	-0.43
2003	4.20	3.01	0.94	-0.06	-0.17	0.65	-0.17
2004	2.75	0.08	1.60	-0.05	0.14	0.72	0.26
2005	1.04	0.75	-0.13	-0.04	0.03	0.35	0.09
2006	2.40	3.13	-1.42	-0.11	-0.19	0.39	0.60
2007	0.32	0.98	-0.34	-0.06	-0.28	0.56	-0.54
2008	-3.29	-2.31	-0.74	-0.08	-0.35	0.69	-0.49
2009	4.70	0.65	3.97	-0.06	-0.18	0.37	-0.06
2010	0.93	-0.98	1.90	-0.09	-0.25	0.43	-0.08
2011	-3.28	-2.08	-1.20	-0.15	-0.14	0.41	-0.11
2012	0.45	-0.98	1.29	-0.04	-0.23	0.25	0.16
2013	1.40	-0.82	2.02	-0.04	-0.16	0.25	0.15
2014	2.95	2.02	1.78	-0.17	-0.30	0.51	-0.89
Total	1.54(2.18)	0.54(1.74)	0.82(1.52)	-0.09(0.04)	-0.16(0.14)	0.58(0.24)	-0.15(0.39)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 8.000 firms of the Belgian manufacturing sector.

Table 6: FHK decomposition - Manufacturing sector - NACE 15-36

Year	△ TFP	Surviving firms			Entry	Exit
		△ Within$_{surv}$	△ Between$_{surv}$	△ Covariance$_{surv}$		
1998	2.32	2.84	-0.16	-0.31	-0.29	0.23
1999	2.98	2.27	0.02	-0.21	0.00	0.91
2000	2.17	1.96	0.10	-0.23	-0.16	0.50
2001	2.87	2.49	0.08	-0.08	-0.20	0.58
2002	1.26	0.79	0.55	-0.18	-0.35	0.47
2003	4.20	3.12	0.94	-0.13	-0.21	0.48
2004	2.75	1.81	0.04	-0.16	0.11	0.95
2005	1.04	0.19	0.63	-0.21	-0.01	0.43
2006	2.40	1.70	0.17	-0.15	-0.29	0.97
2007	0.32	1.24	-0.43	-0.16	-0.34	0.02
2008	-3.29	-2.77	-0.03	-0.22	-0.45	0.19
2009	4.70	1.88	2.66	0.07	-0.22	0.31
2010	0.93	1.38	-0.27	-0.18	-0.34	0.34
2011	-3.28	-3.05	-0.09	-0.12	-0.32	0.30
2012	0.45	-0.43	1.06	-0.32	-0.27	0.41
2013	1.40	0.75	0.63	-0.19	-0.19	0.40
2014	2.95	3.58	0.36	-0.17	-0.45	-0.37
Total	1.54(2.18)	1.16(1.84)	0.37(0.72)	-0.17(0.09)	-0.23(0.15)	0.42(0.33)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 8.000 firms of the Belgian manufacturing sector.

6.5 Decomposition for services sector

Table 7: MP decomposition - Services sector - NACE 50-74

Year	△ TFP	Surviving firms		Entering firms		Exiting firms	
		△ $\overline{TFP}_{surv}$	△ Cov(TFP,MS)$_{surv}$	$\overline{TFP}_{entr_t-surv_t}$	Cov(TFP,MS)$_{entry_t-surv_t}$	$\overline{TFP}_{surv_{t-1}-exit_{t-1}}$	Cov(TFP,MS)$_{surv_{t-1}-exit_{t-1}}$
1998	-2.25	-2.64	0.26	-0.63	-0.19	1.51	-0.56
1999	1.88	1.20	0.66	-0.70	-0.26	1.39	-0.41
2000	0.21	-1.48	1.09	-0.53	-0.16	1.72	-0.44
2001	1.00	-1.38	1.86	-0.54	-0.28	2.06	-0.73
2002	1.07	-0.26	0.91	-0.45	-0.31	1.93	-0.75
2003	0.54	0.36	0.82	-0.38	-0.16	1.81	-1.90
2004	0.56	-0.75	1.24	-0.35	-0.28	1.02	-0.31
2005	-0.03	-0.62	0.58	-0.46	-0.29	1.16	-0.40
2006	1.42	1.15	-0.15	-0.43	-0.06	0.95	-0.04
2007	2.31	2.57	-0.19	-0.35	-0.31	0.70	-0.11
2008	-1.40	-1.76	0.54	-0.47	-0.31	0.89	-0.28
2009	0.92	0.88	0.31	-0.53	-0.32	0.88	-0.30
2010	-0.41	1.64	-0.46	-0.50	-0.33	1.34	-2.10
2011	-0.29	-0.18	0.18	-0.59	-0.23	0.68	-0.14
2012	-2.65	-2.37	0.08	-0.57	-0.22	0.81	-0.38
2013	0.91	1.09	-0.14	-0.44	-0.16	0.65	-0.09
2014	1.24	-0.54	1.73	-0.73	0.08	0.75	-0.06
Total	0.30(1.36)	-0.18(1.47)	0.55(0.67)	-0.51(0.11)	-0.22(0.11)	1.19(0.47)	-0.53(0.59)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 55.000 firms of the Belgian services sector.

Table 8: FHK decomposition - Services sector - NACE 50-74

Year	△ TFP	Surviving firms			Entry	Exit
		△ Within$_{surv}$	△ Between$_{surv}$	△ Covariance$_{surv}$		
1998	-2.25	-1.64	0.30	-0.96	-0.86	0.90
1999	1.88	2.05	0.43	-0.65	-0.89	0.94
2000	0.21	-0.13	0.55	-0.78	-0.67	1.23
2001	1.00	0.65	0.55	-0.68	-0.78	1.26
2002	1.07	0.93	0.54	-0.81	-0.71	1.13
2003	0.54	1.48	0.34	-0.67	-0.52	-0.09
2004	0.56	0.71	0.40	-0.63	-0.60	0.69
2005	-0.03	0.13	0.45	-0.63	-0.73	0.74
2006	1.42	1.69	0.06	-0.78	-0.44	0.88
2007	2.31	2.96	0.05	-0.70	-0.58	0.57
2008	-1.40	-0.76	0.17	-0.60	-0.80	0.59
2009	0.92	1.26	0.48	-0.57	-0.81	0.56
2010	-0.41	1.51	0.25	-0.61	-0.82	-0.74
2011	-0.29	0.44	0.38	-0.83	-0.80	0.53
2012	-2.65	-2.09	0.48	-0.62	-0.84	0.42
2013	0.91	1.01	0.69	-0.77	-0.57	0.55
2014	1.24	1.38	0.49	-0.71	-0.59	0.67
Total	0.30(1.36)	0.68(1.29)	0.39(0.18)	-0.70(0.10)	-0.71(0.13)	0.64(0.48)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 55.000 firms of the Belgian services sector.

6.6 Additional Information

Table 9: Number of incumbent, entering and exiting firms

Year	Incumbent firms	Entering firms	Exiting firms
1997	29871	3192	1687
1998	31376	2000	1803
1999	31573	1974	1796
2000	31751	1956	1782
2001	31925	1866	1649
2002	32142	2010	1407
2003	32745	2171	1200
2004	33716	2143	1075
2005	34784	2542	983
2006	36343	2707	1003
2007	38047	2808	1158
2008	39697	3119	1196
2009	41620	3055	1116
2010	43559	2955	1132
2011	45382	3563	1290
2012	47655	3562	1438
2013	49779	2860	2084
2014	50555	3314	

Notes: The year of entry is defined as the first year of economic activity and the year of exit as the last year of economic activity. We are unable to distinguish mergers and acquisitions from entry and exit, see Geurts (2015) for a discussion on this issue.

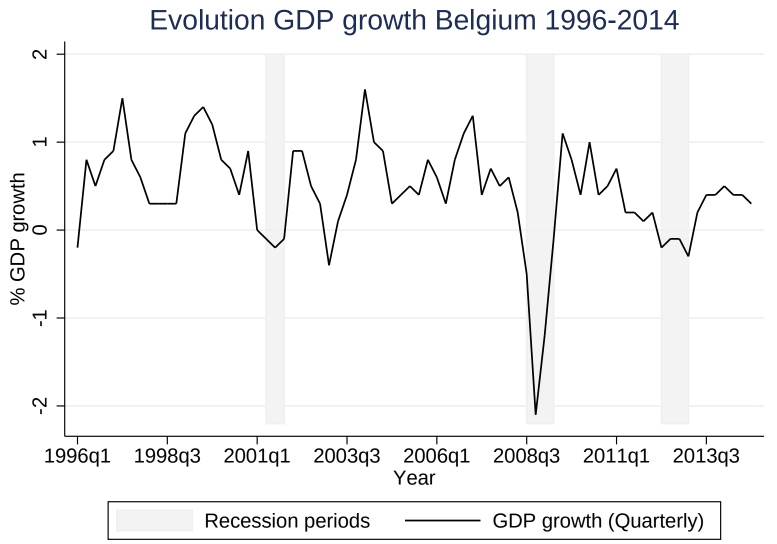
Table 10: Covariances between market share and productivity

Year	Cov(TFP,MS)$_{surv}$	Cov(TFP,MS)$_{entry}$	Cov(TFP,MS)$_{exit}$
1997	0.06	0.04	0.21
1998	0.07	0.00	0.11
1999	0.08	0.05	0.19
2000	0.09	0.04	0.24
2001	0.11	-0.01	0.27
2002	0.12	-0.04	0.46
2003	0.12	0.04	0.19
2004	0.13	0.06	0.26
2005	0.14	0.05	0.12
2006	0.14	0.08	0.26
2007	0.13	-0.01	0.29
2008	0.13	-0.00	0.26
2009	0.15	0.02	0.71
2010	0.14	0.00	0.23
2011	0.13	0.05	0.25
2012	0.15	0.04	0.15
2013	0.15	0.05	0.26
2014	0.17	0.13	
Total	0.12	0.03	0.24

Notes: The covariance for the exiting firms is for the firms that exit in t, and hence is included in the calculation for productivity growth between t and $t+1$. The covariances from this table should not be compared to those reported in figure (12). The covariances reported in this table are calculated based on the entire sample, while those reported in figure (12) are calculated at the industry level and aggregated afterwards, which explains why they are substantially higher.

7 Figures

Figure 1: Recession periods Belgium



Notes: Data on the evolution of GDP in Belgium was obtained from the economic indicators published by the National Bank of Belgium. The gray areas represent recession periods, i.e. periods in which GDP growth was negative for two consecutive quarters. Over our sample period, there were three such periods: Q1-2001 - Q4-2001; Q3-2008 - Q2-2009; Q2-2012 - Q1-2013.

Figure 2: TFP evolution Belgium economy

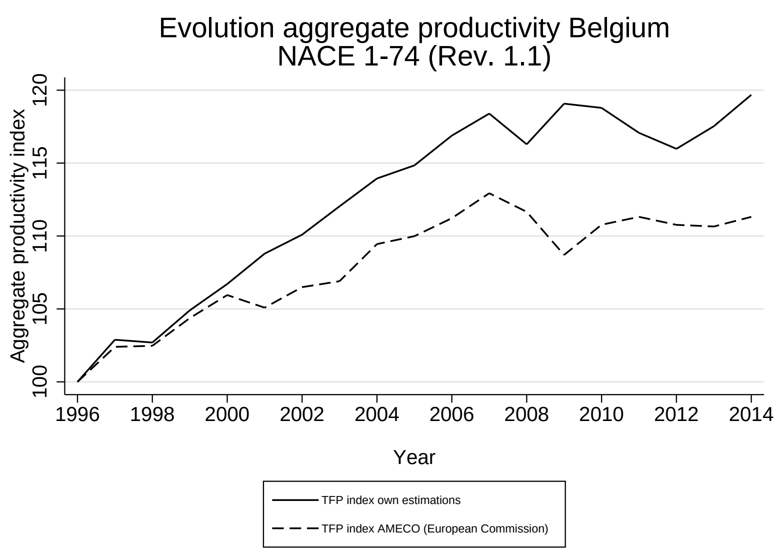
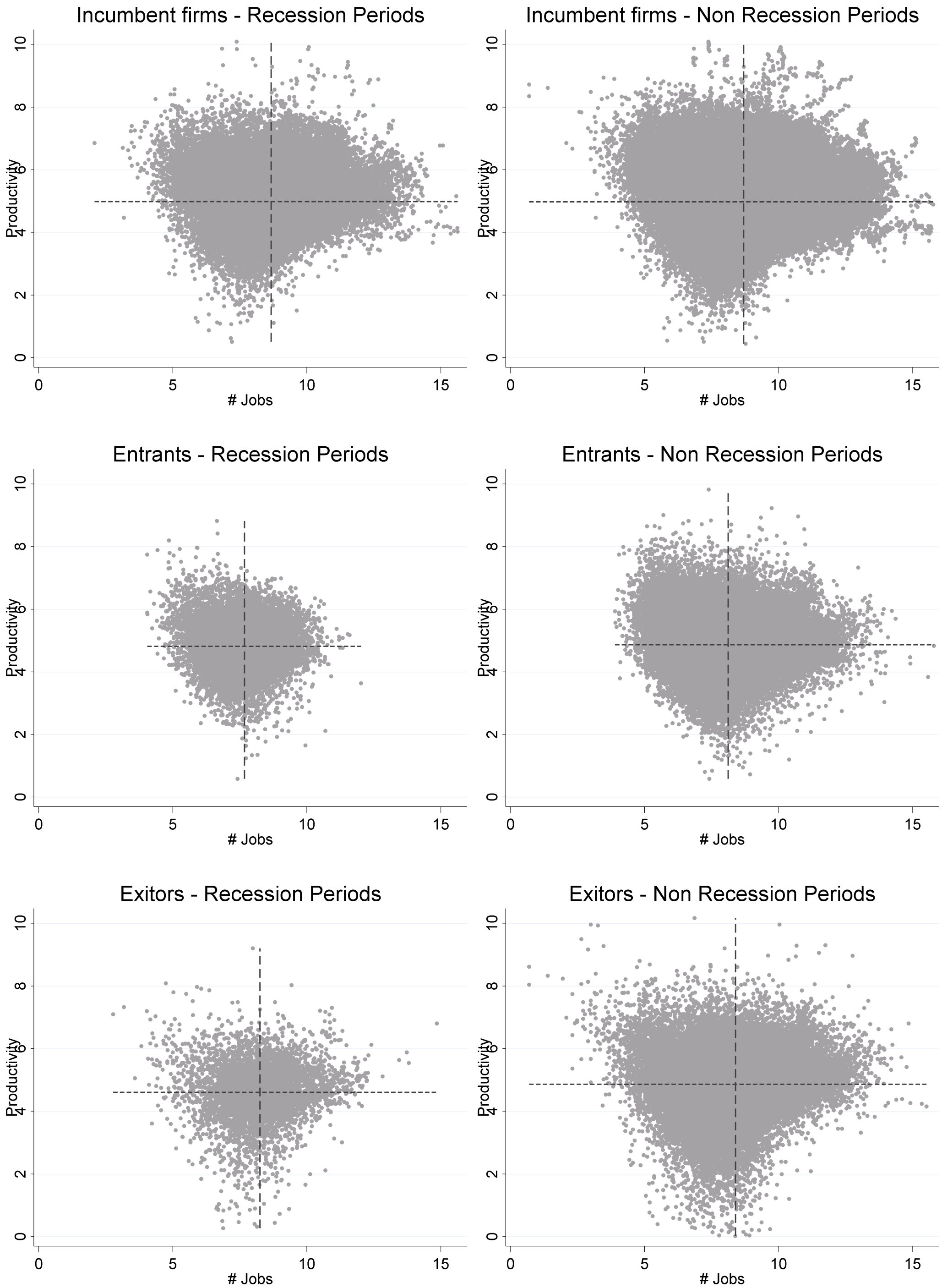
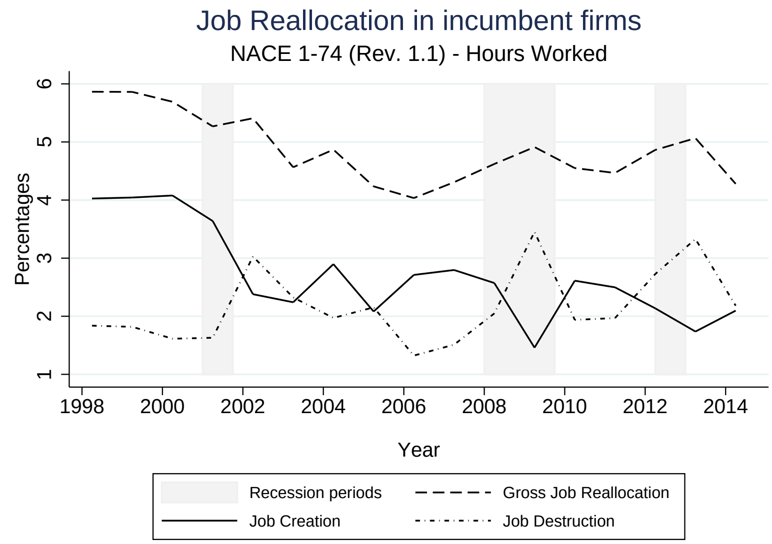


Figure 3: Scatterplots TFP and Jobs



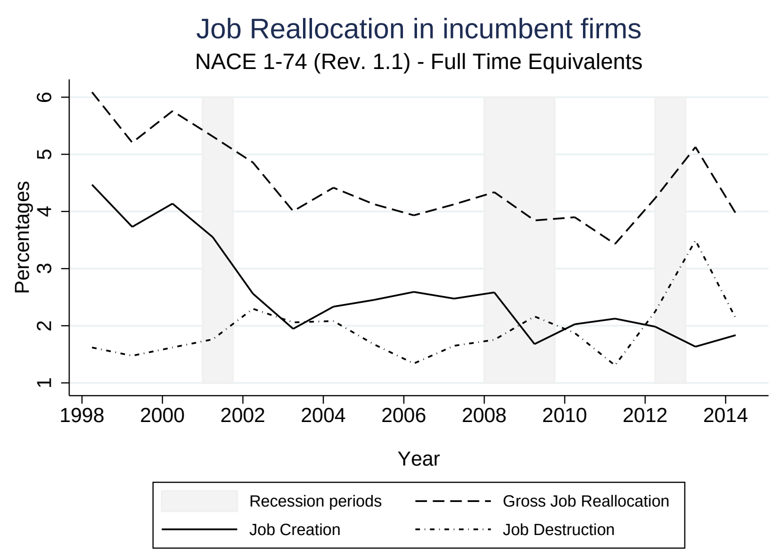
Notes: Scatter plots of TFP and Jobs (both in natural logarithms). Jobs are expressed in hours worked. The dashed lines are the averages of productivity and # jobs. The covariance between productivity and # jobs increases when more firms move towards the first and third quadrant of these scatter plots. Note that simply regarding changes in covariances does not allow to distinguish between changes in TFP and changes in # jobs.

Figure 4: Job reallocation - In Hours Worked



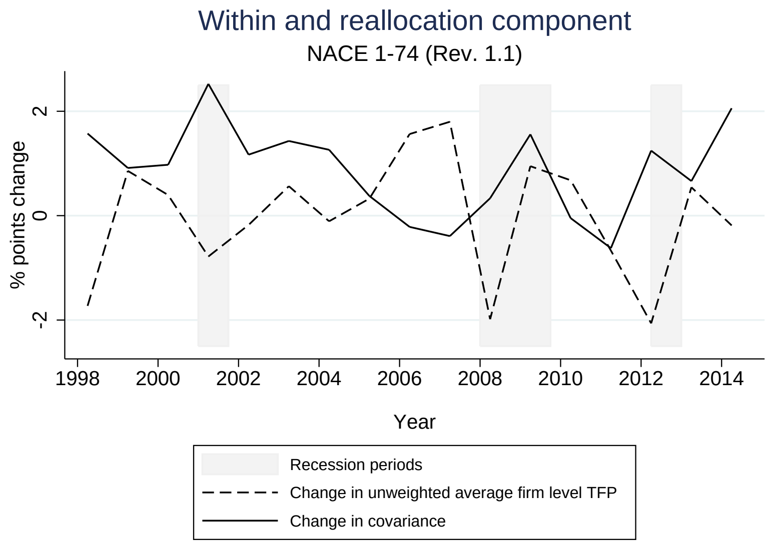
Notes: Job reallocation measures are based on changes in hours effectively worked, so job flows represent changes actual time worked (see section B.3.2 for a discussion). Job creation, job destruction and gross job reallocation are constructed as in Davis and Haltiwanger (1992).

Figure 5: Job reallocation - In FTE's



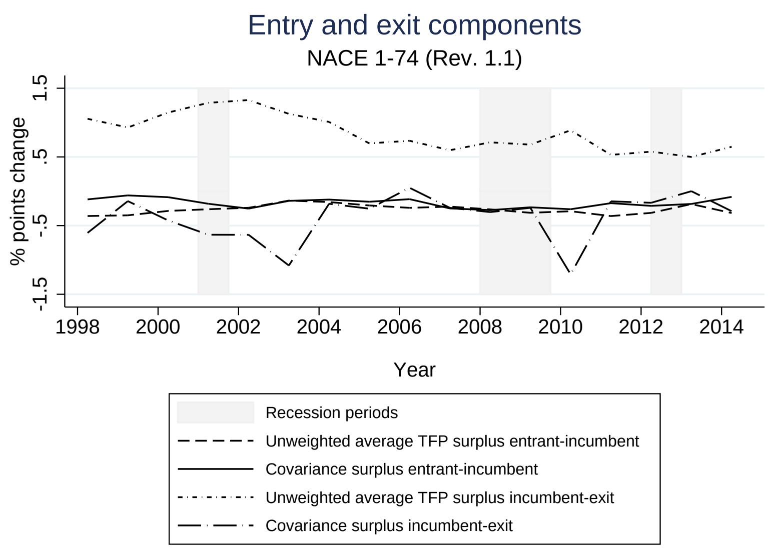
Notes: Job reallocation measures are based on changes in full time equivalents, so job flows represent changes in the number of registered employees expressed in full time equivalents (see section B.3.2 for a discussion). Job creation, job destruction and gross job reallocation are constructed as in Davis and Haltiwanger (1992).

Figure 6: Economy-wide decomposition MP - Incumbent firms



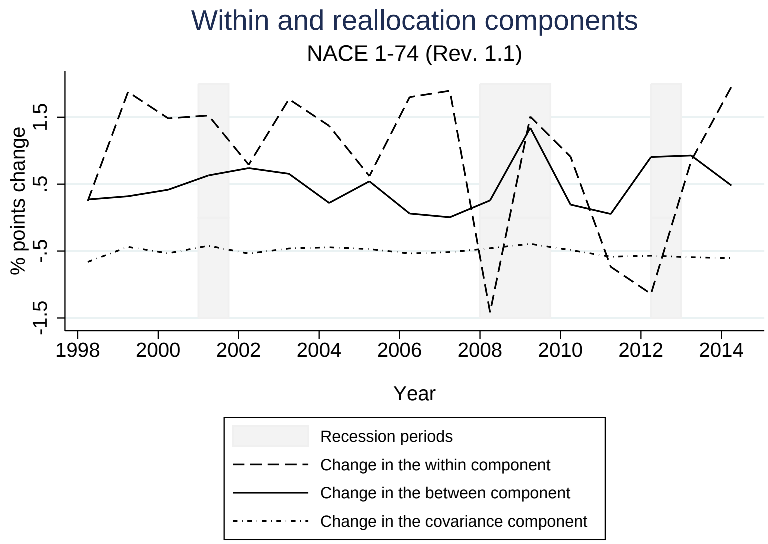
Notes: This graph plots the numbers from table (2).

Figure 7: Economy-wide decomposition MP - Entering and exiting firms



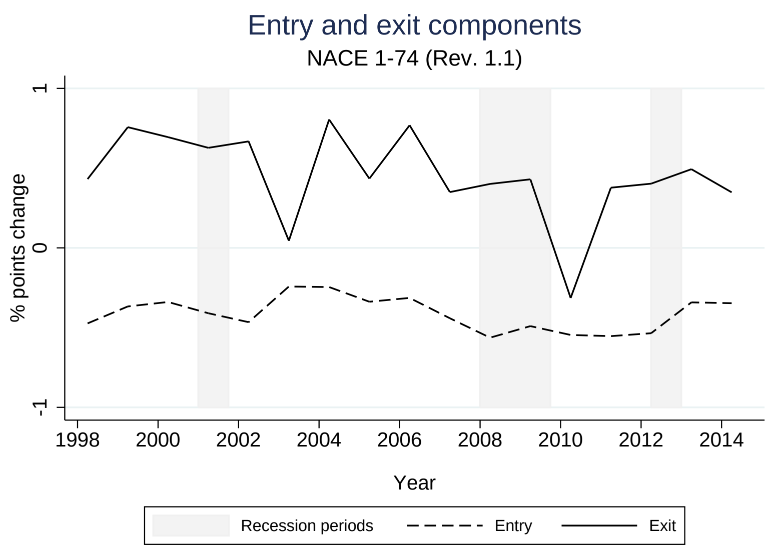
Notes: This graph plots the numbers from table (2).

Figure 8: FHK - Incumbent firms



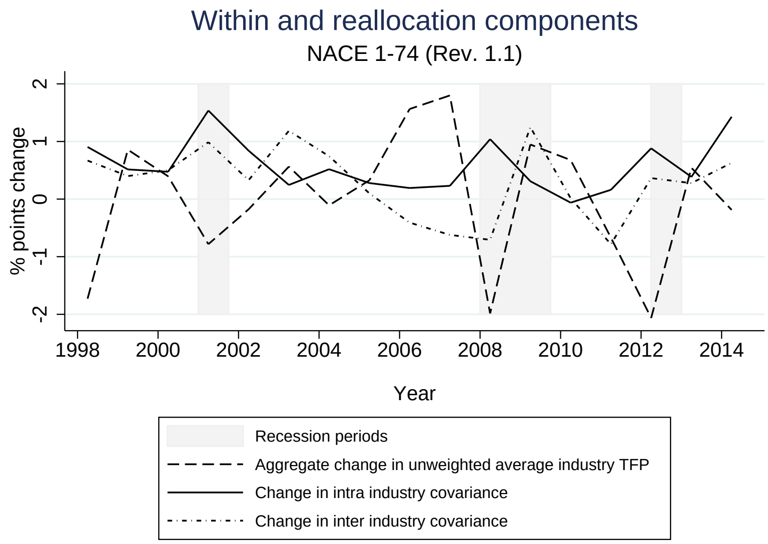
Notes: This graph plots the numbers from table (3).

Figure 9: FHK - Entering and exiting firms



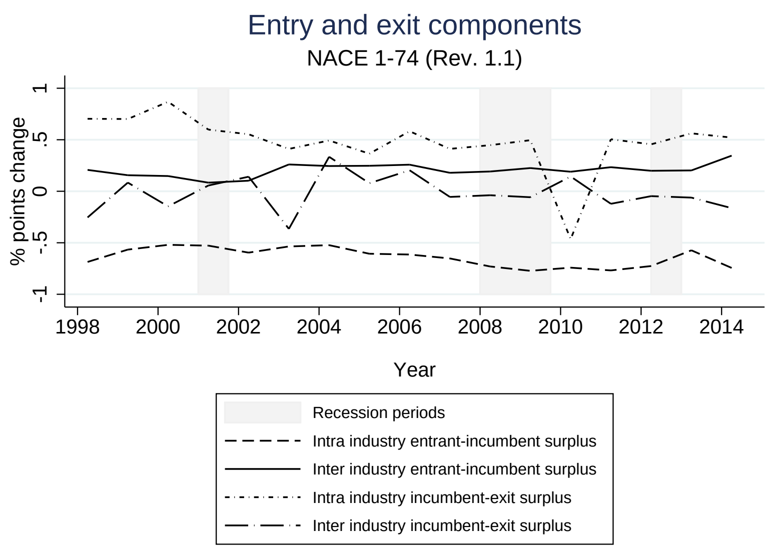
Notes: This graph plots the numbers from table (3).

Figure 10: Industry decomposition MP - Incumbent firms



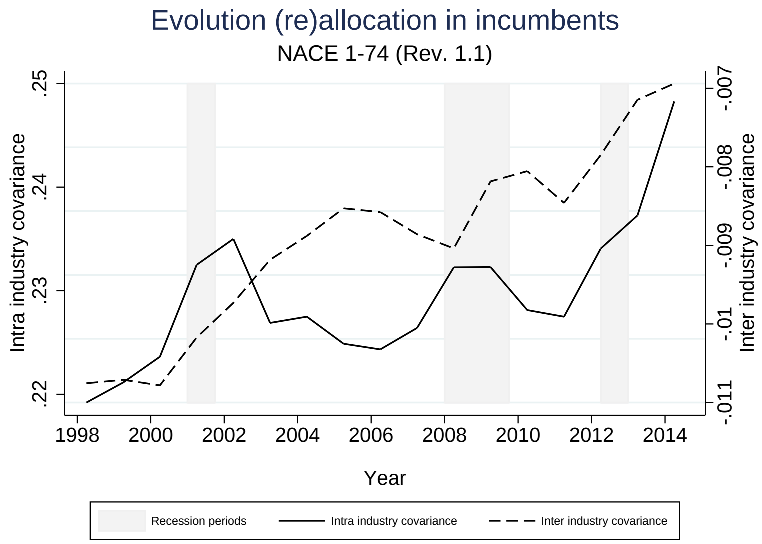
Notes: This graph plots the numbers from table (4).

Figure 11: Industry decomposition MP - Entering and exiting firms



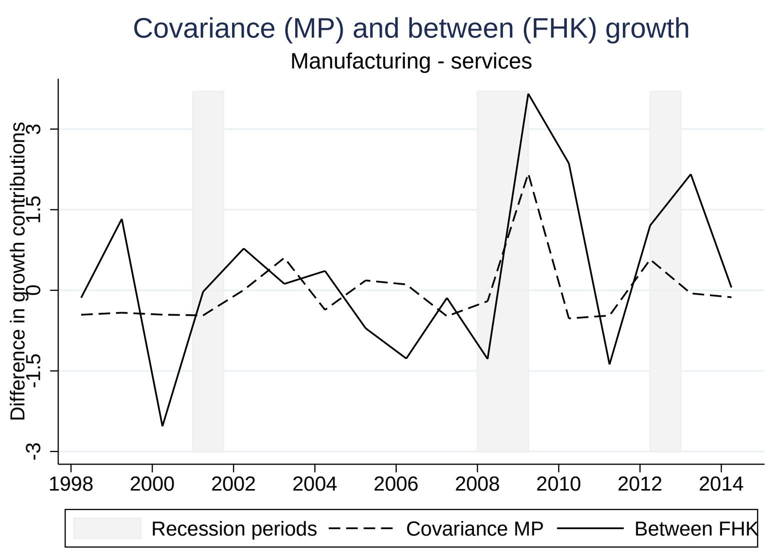
Notes: This graph plots the numbers from table (4).

Figure 12: Covariance between job changes and productivity changes



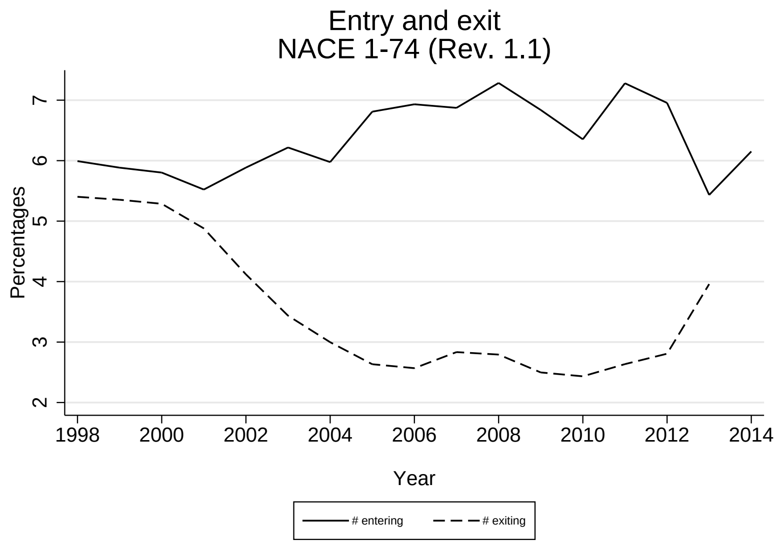
Notes: Inter and intra industry covariances between jobs and productivity.

Figure 13: Cleansing in manufacturing vs. services



Notes: This graph plots the difference in the covariance component of the MP decomposition, i.e. $\Delta Cov(TFP, MS)_{surv,manufacturing} - \Delta Cov(TFP, MS)_{surv,services}$, and the difference in the between component of the FHK decomposition, i.e. $\Delta Between_{surv,manufacturing} - \Delta Between_{surv,services}$.

Figure 14: Entry and Exit in sample



Notes: This graph shows entry and exit expressed relative to the number of active firms in a year. These figures are based on our sample for the decompositions, so after having removed firms that report badly or report negative value added since such observations cannot be used in the decompositions.

8 Appendix

A Robustness checks

The main body of the paper presents results that are based on value added productivity measures, which are aggregated with market shares expressed in hours worked. As argumented, these productivity and aggregation measures are most appropriate for the insights we pursue in this paper. This section presents some robustness checks by making the same decompositions based on alternative productivity and weighting measures.

A.1 Translog production function

The translog production function is more flexible than the standard Cobb Douglas production function since it does not impose separability between the inputs of the production function by including interaction terms between inputs. Moreover, the functional form of this production function is more flexible as it allows the elasticities to vary between firms. See section B.2 for more information on the estimation.

Table A1: MP decomposition - NACE 1-74

Year	△ TFP	Surviving firms		Entering firms		Exiting firms	
		△ $\overline{TFP}_{surv}$	△ Cov(TFP,MS)$_{surv}$	$\overline{TFP}_{entr_t-surv_t}$	Cov(TFP,MS)$_{entry_t-surv_t}$	$\overline{TFP}_{surv_{t-1}-exit_{t-1}}$	Cov(TFP,MS)$_{surv_{t-1}-exit_{t-1}}$
1998	-0.14	-1.66	1.13	-0.15	0.52	1.37	-1.35
1999	3.61	0.80	1.85	-0.05	0.59	1.16	-0.74
2000	2.80	0.23	1.70	0.03	0.39	1.41	-0.96
2001	2.63	-0.84	2.70	0.10	0.51	1.54	-1.39
2002	1.58	-0.33	1.60	0.04	0.40	1.46	-1.59
2003	2.63	0.42	2.17	0.26	0.58	1.33	-2.13
2004	3.04	-0.17	2.24	0.13	0.45	1.19	-0.79
2005	2.09	0.31	1.11	0.09	0.50	0.68	-0.61
2006	3.47	1.46	0.35	0.06	0.70	0.79	0.10
2007	3.15	1.70	0.44	-0.06	0.55	0.71	-0.18
2008	-0.54	-2.10	0.44	0.01	0.56	0.84	-0.29
2009	5.09	0.88	3.58	-0.06	0.58	0.72	-0.59
2010	0.61	0.43	0.07	-0.06	0.43	0.79	-1.05
2011	-0.70	-0.95	-0.10	-0.20	0.62	0.54	-0.61
2012	-0.29	-2.23	1.56	-0.15	0.60	0.58	-0.66
2013	1.35	0.13	0.74	-0.03	0.39	0.51	-0.39
2014	1.74	-0.97	2.69	-0.16	0.72	0.46	-1.00
Total	1.89(1.66)	-0.17(1.15)	1.43(1.04)	-0.01(0.12)	0.53(0.10)	0.95(0.37)	-0.84(0.55)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

Table A2: FHK decomposition - NACE 1-74

Year	△ TFP	Surviving firms			Entry	Exit
		△ Within$_{surv}$	△ Between$_{surv}$	△ Covariance$_{surv}$		
1998	-0.14	0.31	0.03	-0.86	0.37	0.02
1999	3.61	1.75	1.49	-0.63	0.59	0.40
2000	2.80	1.31	1.26	-0.67	0.46	0.44
2001	2.63	1.27	1.18	-0.62	0.64	0.15
2002	1.58	0.39	1.54	-0.69	0.46	-0.13
2003	2.63	1.55	1.58	-0.59	0.87	-0.78
2004	3.04	1.31	1.30	-0.58	0.62	0.38
2005	2.09	0.80	1.18	-0.58	0.63	0.07
2006	3.47	1.61	0.83	-0.66	0.81	0.88
2007	3.15	1.74	1.01	-0.64	0.54	0.51
2008	-0.54	-1.75	0.68	-0.57	0.55	0.54
2009	5.09	1.51	3.41	-0.55	0.60	0.12
2010	0.61	0.23	0.87	-0.61	0.37	-0.25
2011	-0.70	-1.34	0.97	-0.66	0.40	-0.07
2012	-0.29	-1.45	1.47	-0.68	0.43	-0.07
2013	1.35	0.41	1.14	-0.71	0.38	0.12
2014	1.74	1.27	1.12	-0.71	0.59	-0.53
Total	1.89(1.66)	0.64(1.15)	1.24(0.67)	-0.65(0.07)	0.55(0.15)	0.11(0.41)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

A.2 Labor Productivity

Given our interest in the relation between job flows and productivity, we also include the decomposition results for labor productivity measures. We define labor productivity as the ratio of value added to the number of hours effectively worked, hence this measure disregards the role of capital in the production process. Nevertheless, it is an intuitive measure of firm performance that does not require to estimate production functions and hence is not subject to potential biases originating therefrom.

Table A3: MP decomposition - NACE 1-74

Year	$\triangle$ LP	Surviving firms		Entering firms		Exiting firms	
		$\triangle\ \overline{LP}_{surv}$	$\triangle$ Cov(LP,MS)$_{surv}$	$\overline{LP}_{entr_t-surv_t}$	Cov(LP,MS)$_{entry_t-surv_t}$	$\overline{LP}_{surv_{t-1}-exit_{t-1}}$	Cov(LP,MS)$_{surv_{t-1}-exit_{t-1}}$
1998	0.46	-2.60	2.64	-0.17	-0.29	1.13	-0.26
1999	1.96	-0.05	1.61	-0.13	-0.22	0.93	-0.18
2000	1.55	-0.68	1.57	-0.06	-0.27	1.16	-0.17
2001	1.49	-1.76	2.86	-0.08	-0.32	1.22	-0.43
2002	0.98	-1.11	1.49	-0.09	-0.32	1.24	-0.23
2003	1.92	-0.21	1.55	-0.04	-0.36	1.20	-0.22
2004	1.11	-1.08	1.88	-0.04	-0.34	1.03	-0.34
2005	0.76	-0.11	0.62	-0.04	-0.42	0.75	-0.04
2006	1.01	0.51	0.47	-0.05	-0.46	0.84	-0.31
2007	1.01	0.55	0.47	0.00	-0.45	0.70	-0.25
2008	-2.01	-3.05	0.97	-0.04	-0.48	0.81	-0.21
2009	1.65	0.61	1.05	-0.11	-0.49	0.75	-0.16
2010	-1.07	-0.31	0.23	-0.09	-0.52	0.93	-1.31
2011	-2.12	-2.08	-0.04	-0.08	-0.49	0.62	-0.04
2012	-1.75	-3.01	1.27	-0.07	-0.49	0.59	-0.04
2013	0.48	0.17	0.24	-0.11	-0.40	0.55	0.03
2014	0.97	-0.81	1.92	-0.27	-0.54	0.69	-0.02
Total	0.49(1.36)	-0.88(1.22)	1.22(0.84)	-0.09(0.06)	-0.40(0.10)	0.89(0.24)	-0.25(0.30)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

Table A4: FHK decomposition - NACE 1-74

Year	$\triangle$ LP	Surviving firms			Entry	Exit
		$\triangle$ Within$_{surv}$	$\triangle$ Between$_{surv}$	$\triangle$ Covariance$_{surv}$		
1998	0.46	0.18	1.34	-1.46	-0.45	0.84
1999	1.96	1.67	1.03	-1.16	-0.31	0.72
2000	1.55	1.12	1.03	-1.26	-0.30	0.96
2001	1.49	1.26	0.99	-1.16	-0.36	0.75
2002	0.98	0.66	0.95	-1.22	-0.39	0.97
2003	1.92	1.78	0.65	-1.10	-0.36	0.94
2004	1.11	1.25	0.64	-1.09	-0.35	0.67
2005	0.76	0.86	0.73	-1.08	-0.44	0.69
2006	1.01	1.60	0.58	-1.22	-0.47	0.51
2007	1.01	1.64	0.59	-1.23	-0.42	0.44
2008	-2.01	-1.66	0.77	-1.16	-0.55	0.59
2009	1.65	2.13	0.70	-1.19	-0.56	0.58
2010	-1.07	0.53	0.64	-1.25	-0.61	-0.38
2011	-2.12	-1.20	0.57	-1.46	-0.60	0.57
2012	-1.75	-1.27	0.92	-1.35	-0.58	0.54
2013	0.48	0.86	0.98	-1.43	-0.49	0.57
2014	0.97	1.72	0.82	-1.46	-0.76	0.65
Total	0.49(1.36)	0.77(1.15)	0.82(0.21)	-1.25(0.13)	-0.47(0.13)	0.62(0.30)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

A.3 Weighting with FTE's

The tables below show results for jobs measured by full time equivalents instead of hours worked (see section B.3.2 for a discussion).

Table A5: MP decomposition - NACE 1-74

Year	△ TFP	Surviving firms		Entering firms		Exiting firms	
		△ $\overline{TFP}_{surv}$	△ Cov(TFP,MS)$_{surv}$	$\overline{TFP}_{entr_t-surv_t}$	Cov(TFP,MS)$_{entry_t-surv_t}$	$\overline{TFP}_{surv_{t-1}-exit_{t-1}}$	Cov(TFP,MS)$_{surv_{t-1}-exit_{t-1}}$
1998	-0.23	-1.73	1.63	-0.38	-0.11	1.19	-0.82
1999	2.30	0.86	1.03	-0.38	-0.05	0.94	-0.11
2000	1.96	0.40	1.20	-0.31	-0.09	1.16	-0.40
2001	1.96	-0.78	2.50	-0.28	-0.19	1.30	-0.60
2002	1.13	-0.18	1.06	-0.26	-0.25	1.36	-0.61
2003	1.81	0.56	1.55	-0.14	-0.14	1.14	-1.17
2004	2.01	-0.11	1.58	-0.17	-0.15	1.03	-0.17
2005	0.70	0.33	0.27	-0.22	-0.16	0.70	-0.22
2006	1.87	1.56	-0.17	-0.26	-0.10	0.76	0.07
2007	1.31	1.80	-0.35	-0.24	-0.27	0.61	-0.24
2008	-1.81	-1.98	0.26	-0.29	-0.27	0.73	-0.26
2009	1.66	0.95	0.78	-0.34	-0.23	0.69	-0.20
2010	-0.05	0.68	0.16	-0.31	-0.28	0.90	-1.19
2011	-1.04	-0.67	-0.16	-0.40	-0.19	0.55	-0.17
2012	-1.00	-2.06	1.17	-0.35	-0.21	0.61	-0.16
2013	1.14	0.54	0.47	-0.21	-0.18	0.52	0.00
2014	2.10	-0.19	2.38	-0.35	-0.11	0.66	-0.30
Total	0.93(1.28)	-0.00(1.14)	0.90(0.86)	-0.29(0.08)	-0.18(0.07)	0.87(0.28)	-0.38(0.37)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

Table A6: FHK decomposition - NACE 1-74

Year	△ TFP	Surviving firms			Entry	Exit
		△ Within$_{surv}$	△ Between$_{surv}$	△ Covariance$_{surv}$		
1998	-0.23	0.02	0.21	-0.32	-0.50	0.35
1999	2.30	1.74	0.38	-0.24	-0.38	0.80
2000	1.96	1.40	0.48	-0.29	-0.37	0.74
2001	1.96	1.44	0.47	-0.19	-0.44	0.67
2002	1.13	0.63	0.58	-0.33	-0.48	0.72
2003	1.81	1.64	0.70	-0.25	-0.25	-0.03
2004	2.01	1.33	0.42	-0.30	-0.28	0.83
2005	0.70	0.51	0.41	-0.33	-0.36	0.47
2006	1.87	1.73	0.02	-0.39	-0.31	0.82
2007	1.31	1.72	0.03	-0.33	-0.48	0.36
2008	-1.81	-1.55	0.15	-0.28	-0.59	0.46
2009	1.66	1.43	0.50	-0.24	-0.52	0.48
2010	-0.05	0.79	0.39	-0.37	-0.58	-0.28
2011	-1.04	-0.83	0.47	-0.46	-0.60	0.38
2012	-1.00	-1.16	0.66	-0.38	-0.56	0.44
2013	1.14	0.73	0.65	-0.39	-0.36	0.52
2014	2.10	1.86	0.68	-0.40	-0.39	0.36
Total	0.93(1.28)	0.79(1.08)	0.42(0.21)	-0.32(0.07)	-0.44(0.11)	0.48(0.30)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

A.4 Extended MP Decomposition

A.4.1 Translog

Table A7: MP decomposition - Industry to Sector - NACE 1-74

Year	$\triangle$ TFP	Surviving firms			Entering firms		Exiting firms	
		$\triangle\ \overline{TFP}_{surv}$	$\triangle$ Intra Ind Cov(TFP,MS)$_{surv}$	$\triangle$ Inter ind Cov(TFP,MS)$_{surv}$	Intra Ind$_{entr_t-surv_t}$	Inter Ind$_{entr_t-surv_t}$	Intra Ind$_{surv_{t-1}-exit_{t-1}}$	Inter Ind$_{surv_{t-1}-exit_{t-1}}$
1998	-0.14	-1.66	0.83	0.29	-0.54	0.91	0.83	-0.82
1999	3.61	0.80	0.35	1.50	-0.48	1.01	0.81	-0.40
2000	2.80	0.23	0.29	1.41	-0.42	0.84	0.95	-0.50
2001	2.63	-0.84	1.09	1.60	-0.39	1.01	0.83	-0.68
2002	1.58	-0.33	0.71	0.88	-0.45	0.89	0.75	-0.89
2003	2.63	0.42	0.18	1.98	-0.39	1.23	0.69	-1.49
2004	3.04	-0.17	0.31	1.93	-0.40	0.97	0.61	-0.22
2005	2.09	0.31	0.35	0.76	-0.49	1.09	0.73	-0.67
2006	3.47	1.46	-0.06	0.42	-0.62	1.37	0.61	0.29
2007	3.15	1.70	-0.00	0.44	-0.49	0.98	0.47	0.05
2008	-0.54	-2.10	0.80	-0.36	-0.58	1.15	0.44	0.11
2009	5.09	0.88	0.32	3.26	-0.63	1.14	0.56	-0.43
2010	0.61	0.43	-0.42	0.49	-0.63	1.00	-0.96	0.70
2011	-0.70	-0.95	-0.29	0.19	-0.63	1.05	0.48	-0.55
2012	-0.29	-2.23	0.66	0.90	-0.58	1.02	0.46	-0.53
2013	1.35	0.13	0.37	0.37	-0.48	0.84	0.54	-0.41
2014	1.74	-0.97	1.48	1.21	-0.70	1.26	0.52	-1.06
Total	1.89(1.66)	-0.17(1.15)	0.41(0.48)	1.02(0.87)	-0.52(0.10)	1.05(0.15)	0.55(0.42)	-0.44(0.52)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

A.4.2 Labor Productivity

Table A8: MP decomposition - Industry to Sector - NACE 1-74

Year	$\triangle$ LP	Surviving firms			Entering firms		Exiting firms	
		$\triangle\ \overline{LP}_{surv}$	$\triangle$ Intra Ind Cov(LP,MS)$_{surv}$	$\triangle$ Inter ind Cov(LP,MS)$_{surv}$	Intra Ind$_{entr_t-surv_t}$	Inter Ind$_{entr_t-surv_t}$	Intra Ind$_{surv_{t-1}-exit_{t-1}}$	Inter Ind$_{surv_{t-1}-exit_{t-1}}$
1998	0.46	-2.60	1.52	1.12	-0.33	-0.13	0.79	0.09
1999	1.96	-0.05	0.83	0.77	-0.26	-0.09	0.65	0.10
2000	1.55	-0.68	0.79	0.78	-0.21	-0.12	0.85	0.14
2001	1.49	-1.76	1.78	1.08	-0.20	-0.19	0.72	0.06
2002	0.98	-1.11	1.47	0.01	-0.24	-0.18	0.75	0.26
2003	1.92	-0.21	0.83	0.73	-0.19	-0.21	0.73	0.25
2004	1.11	-1.08	0.99	0.88	-0.17	-0.20	0.57	0.11
2005	0.76	-0.11	0.68	-0.06	-0.23	-0.23	0.55	0.16
2006	1.01	0.51	0.65	-0.18	-0.28	-0.22	0.52	0.00
2007	1.01	0.55	0.74	-0.26	-0.21	-0.23	0.43	0.02
2008	-2.01	-3.05	1.48	-0.52	-0.29	-0.23	0.47	0.13
2009	1.65	0.61	0.81	0.24	-0.35	-0.25	0.50	0.09
2010	-1.07	-0.31	0.24	-0.01	-0.40	-0.20	-0.51	0.13
2011	-2.12	-2.08	0.44	-0.48	-0.35	-0.22	0.46	0.12
2012	-1.75	-3.01	1.20	0.08	-0.33	-0.23	0.44	0.10
2013	0.48	0.17	0.22	0.03	-0.28	-0.22	0.48	0.10
2014	0.97	-0.81	1.24	0.68	-0.52	-0.28	0.48	0.19
Total	0.49(1.36)	-0.88(1.22)	0.94(0.45)	0.29(0.54)	-0.28(0.09)	-0.20(0.05)	0.52(0.30)	0.12(0.07)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

A.4.3 Weighting with FTE's

Table A9: MP decomposition - Industry to Sector - NACE 1-74

Year	$\triangle$ TFP	Surviving firms			Entering firms		Exiting firms	
		$\triangle\ \overline{TFP}_{surv}$	$\triangle$ Intra Ind Cov(TFP,MS)$_{surv}$	$\triangle$ Inter ind Cov(TFP,MS)$_{surv}$	Intra Ind$_{entr_t-surv_t}$	Inter Ind$_{entr_t-surv_t}$	Intra Ind$_{surv_{t-1}-exit_{t-1}}$	Inter Ind$_{surv_{t-1}-exit_{t-1}}$
1998	-0.23	-1.73	0.51	1.12	-0.71	0.21	0.62	-0.25
1999	2.30	0.86	0.48	0.56	-0.60	0.16	0.71	0.12
2000	1.96	0.40	0.53	0.67	-0.55	0.15	0.89	-0.12
2001	1.96	-0.78	1.61	0.90	-0.56	0.08	0.63	0.07
2002	1.13	-0.18	0.92	0.14	-0.61	0.10	0.59	0.16
2003	1.81	0.56	0.35	1.20	-0.55	0.27	0.38	-0.41
2004	2.01	-0.11	0.45	1.14	-0.57	0.25	0.50	0.35
2005	0.70	0.33	0.29	-0.02	-0.64	0.25	0.40	0.08
2006	1.87	1.56	0.26	-0.44	-0.62	0.27	0.63	0.21
2007	1.31	1.80	0.21	-0.55	-0.70	0.18	0.42	-0.05
2008	-1.81	-1.98	1.04	-0.77	-0.78	0.22	0.48	-0.01
2009	1.66	0.95	0.28	0.50	-0.80	0.23	0.52	-0.03
2010	-0.05	0.68	-0.07	0.22	-0.79	0.20	-0.40	0.12
2011	-1.04	-0.67	0.25	-0.41	-0.83	0.24	0.51	-0.12
2012	-1.00	-2.06	0.95	0.22	-0.78	0.22	0.49	-0.04
2013	1.14	0.54	0.32	0.15	-0.61	0.22	0.58	-0.06
2014	2.10	-0.19	1.53	0.84	-0.84	0.38	0.53	-0.17
Total	0.93(1.28)	-0.00(1.14)	0.58(0.47)	0.32(0.62)	-0.68(0.11)	0.21(0.07)	0.50(0.26)	-0.01(0.18)

Notes: The naming of the decomposition components is consistent with section 2. The numbers in the table are percentages. The TFP measures are obtained from estimating value added production functions at the two-digit level, additional information on these estimations is provided in appendix B. The decomposition is based on a sample of about 80.000 firms of the Belgian private sector.

B Semiparametric estimation of production functions

The main body of the paper primarily focuses on decomposing aggregate productivity since this is the main instrument to answer the research questions. The focus of this section is on how to obtain the inputs of the decompositions, namely the firm level TFP estimates. In following order we introduce the estimation procedure, elaborate on appropriate data counterparts and present the production function coefficient estimates for each industry.

B.1 Value added production function

In order to obtain productivity measures, we will rely on production functions in which we explicitly assume a functional form for technology. Like many papers in the productivity literature, we rely on a Cobb-Douglas production function to describe the transformation of inputs into outputs. More specifically, output (Y) is generated by two inputs: labor (L) and capital (K), and by the state variable productivity (TFP). These inputs characterize a value added production function. We choose for a value added production function since our data and research objectives favor the use of value added productivity measures (see section B.3.1). The value added Cobb-Douglas production function is given by:

$$Y_{ijt} = TFP_{ijt} * L_{ijt}^{\beta_{lj}} * K_{ijt}^{\beta_{kj}} \tag{1}$$

In which the subscript i refers to firm, j to industry and t to year. TFP_{ijt} represents the productivity of firm i in industry j at year t and L_{ijt}, K_{ijt} are the firm's labor and capital inputs. β_{lj} and β_{kj} are the elasticities of labor and capital. These β-coefficients are indexed by j, indicating that the production function is estimated per industry, in our case at the two-digit level. It is assumed that all firms within an industry have the same technology parameters. Moreover, the Cobb-Douglas production function imposes all TFP differences to be Hicks neutral. In order to estimate this production function, consider the log-linearized transformation:

$$y_{ijt} = \beta_{lj} * l_{ijt} + \beta_{kj} * k_{ijt} + tfp_{ijt} + \epsilon_{ijt} \tag{2}$$

With small letters indicating natural logarithms. The ϵ_{ijt} in this equation is the true exogenous residual output, both for the firm and the econometrician. It contains measurement error and unexpected events to which firms do not react, e.g. bad weather, unforeseen machine breakdowns and strikes.[1] Equations (1) and (2) fundamentally define TFP as the residual in output that is known by the firm but not observed by the econometrician ex ante. In non-econometric terms, TFP is the output that cannot be explained by the return from the capital and labor inputs. Rewriting equation (2) easily allows to obtain the natural logarithm of TFP_{ijt}, which is the input of our decompositions[2]:

$$tfp_{ijt} = y_{ijt} - \beta_{lj} * l_{ijt} - \beta_{kj} * k_{ijt} - \epsilon_{ijt} \tag{3}$$

From equation (3) if follows that we need estimates for β_{lj}, β_{kj} and ϵ_{ijt} in order to calculate tfp_{ijt}. In a moment we show how to obtain $\hat{\epsilon}_{ijt}$. The crux of the matter is to obtain unbiased estimates for β_{lj}

[1] Note that we do not include a constant in equation (2). More accurate would be to write $TFP_{ijt} = \beta_{0j} + tfp_{ijt} + \epsilon_{ijt}$ in which β_{0j} is the average productivity level of all firms in industry j, tfp_{ijt} is the firm specific deviation from this average productivity and ϵ_{ijt} the true exogenous error. In our analysis, we absorb β_{0j} in tfp_{ijt}.

[2] The exponential of this natural logarithm returns TFP in levels. In the literature it is typical to use and decompose weighted average logarithmic productivity measures. Our decomposition methodology would require modification when using levels as inputs. See appendix Melitz and Polanec (2015) for more information and Petrin and Levinsohn (2012) for a further discussion on this topic.

and β_{kj}. Relying on ordinary least squares to obtain estimates for these coefficients is inappropriate because of the well-known problem of endogeneity from a simultaneity bias (Marschak and Andrews, 1944). Firms potentially adapt their use of inputs (l_{ijt}, k_{ijt}) in function of the tfp_{ijt}-part of the residual. This causes biased estimates of β_{lj} and β_{kj}, which in its turn prevents identification of tfp_{ijt}. The idea of semiparametric estimation methods is to overcome the potential simultaneity bias by looking at other firm-specific variables that signal firm-specific information -related to their productivity- to the econometrician. The model of Olley and Pakes (1996, hereafter OP) introduced this insight. According to their model, investments can be used to infer the productivity of a firm.[3] Under relatively mild conditions, it can be shown that investments are a monotonically increasing function of productivity, conditional on capital:

$$inv_{ijt} = f_t(k_{ijt}, tfp_{ijt}) \tag{4}$$

Given the strict monotonicity assumption, the inverse of this investment function can then be used in equation (2) to proxy for tfp_{ijt} under the condition that tfp_{ijt} is the only unobservable that enters the investment function:

$$y_{ijt} = \beta_{lj} * l_{ijt} + \beta_{kj} * k_{ijt} + f_t^{-1}(k_{ijt}, inv_{ijt}) + \epsilon_{ijt} \tag{5}$$

The functional form of $f_t^{-1}(k_{ijt}, inv_{ijt})$ can be very complicated as it has to hold for all firms in the industry, regardless of their characteristics. Therefore, this function is usually treated non-parametrically. In practice this boils down to substituting tfp_{ijt} with a third or fourth order polynomial of k_{ijt} and inv_{ijt}. Levinsohn and Petrin (2003, hereafter LP) argue that it is better to use materials as a proxy variable for unobserved productivity since investments are often zero or lumpy reported. However, due to limited reporting in our data, we rely on investments as proxy variable. Since the inverse of the investment function proxies for unobserved productivity, equation (5) simply allows to identify $\hat{\epsilon}_{ijt}$ as the remaining residual of this equation. According to the model of OP, equation (5) also allows to obtain an unbiased estimate of β_{lj} since they assume labor to be a flexible non-dynamic input that is chosen each period and has no impact on future output of the firm. Furthermore their model assumes capital to be a dynamic input that is subject to an investment process. Capital at t is determined at $t-1$ and it takes one period for capital to become productive. Under these assumptions, equation (5) allows unbiased identification of β_{lj} since there is no simultaneity between the choice of labor and the other variables in equation. Ackerberg et al. (2015, hereafter ACF) argue that the flexible input assumption of labor is problematic. This is indeed arguable, especially for a rather rigid labor market like the one in Belgium.[4] To identify the labor coefficient, they propose to rely on the same assumption as OP and LP use for the identification of the capital coefficient, which is that productivity evolves according to a first order Markov process:

$$tfp_{ijt} = E[tfp_{ijt}|I_{ijt-1}] + \xi_{ijt} = E[tfp_{ijt}|tfp_{ijt-1}] + \xi_{ijt} \tag{6}$$

In which I_{ijt-1} is the information set of the firm at $t-1$. This assumption implies that a firm's expectations on future productivity only depend on its current productivity. So by assumption all elements of I_{ijt-1} are orthogonal to ξ_{ijt}, which is the unexpected innovation in productivity. Since

[3] An important assumption of the OP methodology is that investments become part of the capital stock after one period. Section B.3.3 expands on the construction of the capital stock and investments.

[4] If labor would be chosen before investments, it would become part of the investment function: $inv_{ijt} = f_t(l_{ijt}, k_{ijt}, tfp_{ijt})$. It is obvious that in this scenario, the equivalent of equation (5) would not allow identification of β_l.

k_{ijt} is actually decided at $t-1$, it is in I_{ijt-1}. Although l_{ijt} is not in I_{ijt-1} since it is decided at t (OP,LP) or between $t-1$ and t (ACF), l_{ijt-1} can be used as an instrument for l_{ijt} since it is in I_{ijt-1}. Together, these form the following moment conditions:

$$E\left[\xi_{ijt}(\beta_{lj},\beta_{kj})\cdot\begin{pmatrix}k_{ijt}\\ l_{ijt-1}\end{pmatrix}\right]=0 \tag{7}$$

ACF use the sample analogue of these moment conditions to obtain consistent estimates for the capital and labor coefficients. Practically, this can be done by estimating equation (5) to obtain $\hat{\epsilon}_{ijt}$ and initial values for $\hat{\beta}_{lj}$ and $\hat{\beta}_{kj}$, which allows to construct an initial estimate for tfp_{ijt} from equation (3). Non-parametric regression of $\widehat{tfp}_{ijt}$ on $\widehat{tfp}_{ijt-1}$ then returns an estimate for $\xi_{ijt}(\beta_{lj},\beta_{kj})$. These estimates can be used to bring the sample analogue of equation (7) as close to zero as possible, through which consistent estimates for β_{lj} and β_{kj} are found. Wooldridge (2009) showed how this set of assumptions also allows to obtain coefficient estimates for β_{lj} and β_{kj} with a one step GMM estimator that is more efficient, does not require bootstrapping to obtain standard errors and capitalizes more from the orthogonality of ϵ_{ijt}. When applying the Markov process-assumption on the evolution of productivity to equation (5) we obtain:

$$y_{ijt}=\beta_{lj}*l_{ijt}+\beta_{kj}*k_{ijt}+f_t^{-1}(k_{ijt-1},inv_{ijt-1})+\xi_{ijt}+\epsilon_{ijt} \tag{8}$$

In this equation there is no simultaneity bias since the proxy for unobserved productivity now consists of a non-parametric function of the lag of capital and the lag of investments. Moreover, k_{ijt} is orthogonal to ξ_{ijt} and ϵ_{ijt}. Although labor is uncorrelated with ϵ_{ijt}, it will be correlated with ξ_{ijt} if it has a dynamic nature and is chosen between $t-1$ and t. This can be solved by instrumenting l_{ijt} with l_{ijt-1}. In practice, equation (8) allows to obtain consistent coefficient estimates by using pooled IV in which the labor variable is instrumented with its lag, the capital variable serves as its own instrument and the non-parametric function is modeled as a fourth order polynomial in the lags of capital and investments. Since the Wooldridge (2009) procedure is very pragmatic, it is our preferred method to estimate production functions. In conclusion, tfp_{ijt} can be retrieved by estimating equation (5) to obtain $\hat{\epsilon}_{ijt}$ and equation (8) to obtain $\hat{\beta}_{lj}$ and $\hat{\beta}_{kj}$. Substituting these estimates into equation (3) returns firm level TFP estimates. In practice, we deviate from this procedure by ignoring the true exogenous error. Given our interest in aggregate productivity, we aim to obtain TFP estimates for a sample as large as possible. Following the procedure above requires reporting on value added, labor, capital and investments. However, due to the definition of investments, there are no investments available in the first year of the sample. If we would furthermore drop the firms for which investments are not available in a certain year, we end up loosing 30% of our sample. Moreover, as theoretically expected, $\hat{\epsilon}_{ijt}$ is on average zero in our sample. Therefore, we choose to use TFP measures that also include ϵ_{ijt}. Since this approach does not require data on investments to calculate TFP measures, this allows using a larger and more representative sample.[5,6]

[5] Note that data on investments is required to estimate the production function. However, once the labor and capital coefficients are calculated at the industry level, we can use these to calculate firm level TFP measures for all firms that report value added, labor and capital.

[6] We did our analyses on the sample for which we have investments reported for all years with and without correction for the true exogenous error and the findings are robust.

B.2 Gross output and Translog production function

Since gross output and translog production functions are used in robustness checks (see section A), we briefly expand on how these are estimated. The same set of assumptions and the Wooldridge (2009) estimator, which were introduced for the Cobb-Douglas production function in the previous section, again underlie the estimation procedure.

Gross output - The gross output production function differs from the value added production function by including intermediate inputs (m_{ijt}) as input in the production function. The inclusion of intermediate inputs on top of labor and capital precludes one from assuming a fixed proportion of intermediate inputs for a unit of output. In value added production functions, firms cannot increase output by increasing intermediate inputs, conditional on labor, capital and productivity, i.e. value added production functions are Leontief in intermediate inputs. Gross output production functions are more flexible in this regard.[7] The equivalent of equation (8) is then:

$$y_{ijt} = \beta_{lj} * l_{ijt} + \beta_{kj} * k_{ijt} + \beta_{mj} * m_{ijt} + f_t^{-1}(k_{ijt-1}, inv_{ijt-1}) + \xi_{ijt} + \epsilon_{ijt} \tag{9}$$

In which y_{ijt} now represents gross output instead of value added. We follow LP and ACF in their timing assumptions. Intermediate inputs are modeled as flexible inputs that are chosen at time t. Hence equation (9) does not suffer from simultaneity issues and allows identification of β_{mj}. As in the value added case, this equation is estimated with pooled IV in which labor is instrumented with its lag. Capital and materials serve as their own instruments and the proxy function for unobserved productivity is modeled with a fourth order polynomial in lagged capital and investments.[8] The coefficient estimates from this equation can then be used to calculate tfp_{ijt}[9]:

$$tfp_{ijt} = y_{ijt} - \hat{\beta}_{lj} * l_{ijt} - \hat{\beta}_{kj} * k_{ijt} - \hat{\beta}_{mj} * m_{ijt} \tag{10}$$

Translog - The translog production function is a generalisation of the Cobb-Douglas production function. It does not impose separability between the inputs of the production function by including interaction terms between inputs. Moreover, the functional form of this production function is more flexible as it allows the elasticities to vary between firms. The Translog equivalent of equation (8) is given by:

$$y_{ijt} = \beta_{l1j}*l_{ijt}+\beta_{l2j}*l_{ijt}^2+\beta_{k1j}*k_{ijt}+\beta_{k2j}*k_{ijt}^2+\beta_{lkj}*k_{ijt}*l_{ijt}+f_t^{-1}(k_{ijt-1}, inv_{ijt-1})+\xi_{ijt}+\epsilon_{ijt} \tag{11}$$

The same timing assumptions as in the previous section apply. Hence by using a pooled IV estimator in which labor is instrumented with its lag and capital serves as its own instrument, consistent coefficient estimates can be obtained. To obtain firm level TFP estimates, hese can subsequently be substituted into the following equation:

$$tfp_{ijt} = y_{ijt} - \hat{\beta}_{lj} * l_{ijt} - \hat{\beta}_{l2j} * l_{ijt}^2 - \hat{\beta}_{kj} * k_{ijt} - \hat{\beta}_{k2j} * k_{ijt}^2 - \hat{\beta}_{lkj} * l_{ijt} * k_{ijt} \tag{12}$$

[7] This seems to favor the use of gross output production functions. Nonetheless, Bond and Söderbom (2005) showed for the Cobb Douglas case and Gandhi et al. for the more general case that the identification of flexible inputs can be problematic. They argue that gross output production functions cannot be identified without imposing additional assumptions on the model.

[8] If one wants to treat intermediate inputs as a dynamic input that is chosen between $t-1$ and t, then m_{ijt} will be correlated with part of ξ_{ijt} and m_{ijt} must be instrumented with its lag in order to obtain an unbiased estimate for β_{mj}.

[9] Again we ignore the true exogenous error as this does not alter our findings and allows to obtain firm level TFP estimates for a larger sample. Also for the Translog production function, we will ignore this true exogenous error.

B.3 Output and inputs of the production function

Our data is mainly from a dataset from the National Bank of Belgium that contains annual accounts of all firms in Belgium with limited liability. This section presents a detailed overview of the variables that were selected from this dataset as data counterparts for the variables introduced in Appendix B.1. Also deflation, data cleaning and specific issues on data with regard to the empirical analysis are discussed.

B.3.1 Output

Either gross output or value added can be used as output measure in production functions. Gross output is a measure of the total sales and receipts. At the level of an economy, aggregate gross output is the sum of sales to final users in the economy (GDP) and sales to other industries (which then serve as inputs in those industries). Value added can be obtained by subtracting goods and services purchased from other firms from gross output. Value added includes wages, interest, depreciation, rent, taxes and profit. According to the national income identity, aggregate value added is equal to aggregate final demand because intermediate inputs cancel out in the aggregate. This means that value added based productivity could be interpreted as a firm's capacity to contribute to final demand. Since we are interested in productivity as a determinant of welfare, which is directly related to aggregate demand, it is intuitive to choose for value added productivity measures. Also from a practical point of view, only firms that are obliged to report full annual accounts have to report gross output and this is only a small part of our sample.[10] In order to represent the Belgian economy in our decompositions, it is important to aim for a sample size that is as large as possible.

Our dataset contains net value added.[11] Two-digit producer price indices (PPI's) are used to obtain real values for the outputs. Over the course of our sample period, the industry classification changed. From 1997-2006 firms are classified in NACE rev. 1.1. and from 2007-2014 in NACE rev. 2. Since the conversion between these two classifications is not a 1:1 relationship, we used a different deflator for each period and use 2006, the year for which both PPI deflators are available in both classifications, as base year. For the period 1997-2006, we rely on a two-digit PPI for all industries from the National Bank of Belgium. For the period 2007-2014, we rely on a two-digit PPI from Eurostat.

[10] A firm has to file full annual accounts when the average annual number of employees is higher than 100 or when at least two of the following thresholds are surpassed: (i) average annual number of employees equal to 50, (ii) turnover (excluding VAT) €7.300.000, (iii) balance sheet total €3.650.000. Only about 8% of the firms meets these requirements.

[11] It also includes gross output measures like turnover (code 70 in the profit and loss account) or operating revenues (code 70-74 in the profit and loss accounts). Gross output can also be calculated by adding intermediary inputs up to value added. Doing so increases the number of observations with reported gross output and the correlation of this constructed gross output measure with reported turnover and operating revenues is respectively 99.7% and 100%.

B.3.2 Labor

To estimate Total Factor Productivity as well as Labor productivity, one needs an accurate proxy for labor. Based on the annual accounts of firms, there are three ways to infer the amount of labor a firm employs. Firms report *the personnel costs* (code 1023 in the social balance sheet), *the number of full time equivalents* (code 9088 in the profit and loss accounts) and *the number of hours actually worked* (code 9087 in the profit and loss accounts).

When estimating production functions, it is important that the labor measure truly reflects the amount of labor employed in the production process. Therefore, it is necessary to carefully examine what the aforementioned labor measures actually represent. It is important to distinguish between whether or not being in the personnel register of the firm. All personnel who are under contract of the firm, are in the personnel register.[12] The *number of full time equivalents* is the sum of all employees in the personnel register, in which part time employment is aggregated to its full time equivalent. However, the number of full time equivalents ignores whether or not an employee is active. So it abstracts from overtime, absence due to sickness, career breaks, unpaid leave, maternity or paternity leave, hours lost due to strikes or other reasons and unemployment because of economic reasons.[13] The *number of hours actually worked* is solely based on active employees. It represents the actual number of salaried hours for those that are registered in the personnel register. Hence this measure is a closer proxy for the amount of labor that is employed in the production process and contributes to the value created by the firm.[14] The *personnel costs* contain all costs related to employees who are in the personnel register.[15] Since there is substantial heterogeneity in wages between firms, the link between personnel costs and the amount of labor employed is not as straightforward as with the number of full time equivalents or the actual number of hours worked. Also, using personnel costs would bring the additional challenge of finding a deflator that captures the wage evolution. Therefore, we opt for the actual number of hours worked as labor input in the production function.

[12] Note that temporary workers are not in the personnel register as they are not directly under contract of the firm. Also directors, managers and associates are only in the personnel register if they have a labor contract with the firm.

[13] The Belgian law allows firms to temporarily reduce employment without firing employees. The national employment office then compensates the loss in wage for the employee. During the great recession, firms heavily used this system to do labor hoarding. Hence the number of full time equivalents would overestimate employment and underestimate job destruction, especially in times of crisis.

[14] Although the official guidelines for reporting strictly define the 'number of hours actually worked', in practice some firms report the theoretical number of hours actually worked, which is simply the product of the number of full time equivalents and the average number of hours worked by one full time equivalent.

[15] Code 62 of the profit and loss account comprises a wider scope of personnel costs, i.e. also additional reimbursements for personnel on early retirement, costs from unregistered personnel that is hired and employed abroad and costs from other personnel who are not in the personnel register. Nevertheless, the costs of temporary workers are not included.

B.3.3 Capital

Capital serves as an input in the production function. As is standard in the productivity literature, our measure for the capital input comprises the tangible fixed assets of the firm (codes 22-27 of the balance sheet). For an extensive discussion on capital inputs for productivity estimations, we refer to Harper (1999).

To obtain the real capital stock from the nominal values in the annual accounts, we apply the Perpetual Inventory Method. For the first year that a firm is in the sample, we deflate the book value of tangible fixed assets with an economy-wide gross fixed capital formation deflator. Thereby we obtain the real capital stock for the first year. For all subsequent years, we define the real capital stock as the depreciated sum of the lagged real capital stock and deflated investments. First, nominal investments are obtained by:

$$Nominal\,Investment_t = Nominal\,Capital_t + Nominal\,Depreciation_t - Nominal\,Capital_{t-1} \quad (13)$$

Depreciations can be found under code 63 in the profit and loss accounts.[16] Since our semiparametric approach to estimate the production function also makes use of investments, this does not reduce the number of observations that can be used to estimate the production function. Nominal investments are then deflated with an economy-wide gross fixed capital formation deflator to obtain real investments. The real capital stock is then calculated as:

$$Real\,Capital_t = (Real\,Capital_{t-1} * (1-\delta)) + Real\,Investment_t \quad (14)$$

In which the depreciation rate $\delta = \dfrac{Nominal\,Depreciation_t}{Nominal\,Capital_t + Nominal\,Depreciation_t}$.

B.3.4 Materials

Levinsohn and Petrin (2003) argued that materials are a good proxy for unobserved productivity in semiparametric estimations of production functions. Unfortunately, only firms that report full annual accounts are obliged to report materials. Since this is only about 7% percent of the firms, this reduces the sample size significantly. Therefore, the use of materials is disregarded.

Materials, or more general 'intermediary inputs', are goods and services (including energy, raw materials, semi-finished goods, and services that are purchased from all sources), other than fixed assets, that are used as inputs into the production process. Codes 60-61 in the profit and loss accounts allow to infer intermediary input use. In order to obtain real values for intermediary inputs, the same two-digit PPI deflator as for outputs can be used.

[16]Using firm-year-specific depreciation will induce variation in investments, which is useful for identification of the capital coefficient when using a one-step estimator for the production function, like we do in this paper.

B.3.5 Additional information

Given the empirical nature of this paper, it is important to provide sufficient information on how we dealt with incomplete and implausible reporting in the annual accounts. Therefore, this section expands on how incomplete accounts for entering and exiting firms are used, how missing data is imputed and on how potential measurement error and outliers are handled. The empirical analysis actually can be split into two steps. The first step is to estimate the production function to obtain industry specific capital and labor coefficients that allow to calculate firm level productivity measures. In a second step, these firm level productivity measures are used in productivity decompositions to infer the micro origins of the evolution of aggregate productivity. The sample of firms is not necessarily the same in these two steps. Once the capital and labor coefficients are obtained, TFP can be calculated for all firms that report positive value added, labor and capital. However, for the estimation of the production function also investments must be reported.

Entry and exit - The productivity decomposition includes an entry and exit component. Entry is defined as a new vat-number that was not in the dataset the year before. Exit is identified from a vat-number that is not in the dataset and was in there a year before. When firms enter or exit in the middle of the year, this is reflected in their annual accounts. Especially 'value added', 'materials' and 'the effective number of hours worked' cannot be compared with firms that report annual accounts based on full-year activity. It is necessary to correct for this, especially with regard to the productivity decompositions. Not doing so could lead to false conclusions, e.g. TFP (which is actually residual value added) of entering and exiting firms will be lower simply because these firms were only active for a couple of months. Ignoring this would probably result in an underestimation of productivity for entering and exiting firms. Therefore, inputs and outputs for entering and exiting firms are rescaled when their annual accounts are not based on twelve months of activity. More specifically, the inputs and outputs of entering and exiting firms are rescaled with a factor 'one divided by the number of months to which the annual account refers times twelve', e.g. values for firms that entered six months before they filed their first annual account are multiplied by a factor two.

Missing data - Firms should file their annual account each year. Nevertheless, it happens occasionally that firms do not report some variables or do not even report their annual accounts at all in a specific year. This entails issues in the analyses, hence a priori cleaning of the data is required. We distinguish between the two steps of the empirical analysis, the estimation of production functions and the decompositions. As we estimate loglinear production functions, the estimator will ignore all observations with negative value added and the observations for which there is missing data on the labor, capital and investment inputs. The decompositions are manually coded and require careful data cleaning a priori to avoid biases from outliers and biases from artificial entry and exit. Obviously, deleting observations with missing data would create artificial entry and exit. Moreover, a lot of the components in the decompositions are constructed from weighted averages. As a result, the decompositions are by nature sensitive to outliers in the aggregation measures. Also, the decomposition uses loglinear productivity and loglinear market share as inputs. This rules out firms that report negative value added and firms that are self employed. So it is necessary to clean the data before doing the decompositions for three sources of bias: artificial entry and exit, outliers that could drive weighted average measures and inappropriate inputs for loglinear transformations.

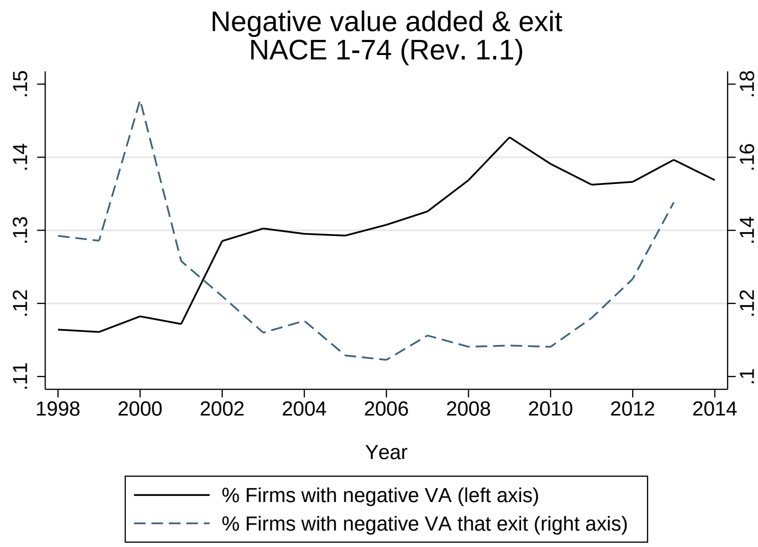
Imputation - One solution for the problem of missing data would be to delete the firm completely from the sample when it does not report one of the necessary variables in a year. However, this is a very rough solution since the chance that one of the necessary variables is missing in one year is fairly high given the long time span of our sample. Therefore, we imputed missing values in a limited number of scenarios. If a variable is not reported in year t but is reported in $t-1$ and $t+1$, we impute the missing variable with the average value of the previous and subsequent year. If a variable is missing for the first year only, we replace it by the value of the second year of economic activity. Similarly, if the last year is missing for a variable, we replace it by the last year of economic activity. If a variable is missing for more than two subsequent years, we delete all the observations of that firm from our sample. Also when the complete annual account is missing for one year, we delete all observations of that firm from our sample. Again, not doing so would again create artificial entry and exit, and bias the aggregate productivity measures so that the components of the decomposition do not sum up to aggregate growth anymore.

Outliers - All analyses rely on data from annual accounts. It is common practice in the productivity literature to trim or winsorize the data and the estimated TFP measures to control for biases resulting from measurement error and to make results robust to outliers. However, there are several reasons for which we choose not to trim or winsorize the upper and lower percentiles of our data and TFP estimates. First, it is empirically established that TFP distributions typically have large tails. However, this does not imply that the TFP measures in the lowest and highest percentiles result from measurement error. TFP measures in the highest percentiles are typically from very large firms, for whom the annual accounts likely contain even less measurement error than those of average sized firms since their annual accounts are filed by professionals. Secondly, these large firms in the upper percentiles matter for the aggregate productivity of an economy, especially in a small and open economy like Belgium. Therefore, these firms should be included in research on aggregate productivity. Thirdly, firms that are in the left tail of the productivity distribution are typically entrants and exiting firms that have low productivity. Deleting these firms from our sample could bias the entry and exit components of the productivity decompositions and consequently result in an overestimation of the contribution from surviving firms to the aggregate productivity evolution.

Measurement error - Of course, outliers that result from measurement errors or mistakes in the annual accounts must be accounted for. Given the aforementioned sensitivity in productivity decompositions from outliers, this is a crucial step in the analysis. We chose to clean our data based on implausible growth rates for productivity, inputs and outputs. More specifically, we first deleted firms that report growth rates in employment or value added higher than a factor 10 as we believe this to be implausible. After removing a small number of firms that report such extreme growth, we also remove firms that are in the highest or lowest percentile of the yearly growth distribution of productivity or one of the inputs or outputs. Firms with less than 10 employees were disregarded from this cleaning rule since for small firms, growth rates can be relatively large. Also exiting firms were disregarded as for such firms large declines in inputs and outputs can be expected. For entering firms, cleaning on growth is not possible since lagged values are not available. Since we did find implausible observations in entering firms, we deleted the firms in the upper and lower percentile of the input and output distribution of entering firms for each industry-year combination.

Sample construction - There are about 600.000 firms in our dataset of the National Bank of Belgium that ranges from 1997-2014. Not all observations can be used, hereby we present a breakdown of how we obtain our sample. First, there are 79.000 firms that do not file annual accounts for at least one of the years they are active on the market. This would show up as exit and entry in the decomposition, so we must delete these firms from the sample. Second, there are about 218.000 firms that report negative value added in at least one year, and who consequently would also have negative TFP. The economic meaning of negative TFP is ambiguous and also the decomposition uses a loglinear transformation of TFP as input, which rules out the use of these observations by construction so this would again result in artificial entry and exit. From the 310.000 remaining firms in our sample, there are about 194.800 firms for which there are no value added (2.800 firms), labor (180.000 firms) or capital (12.000 firms) measures available in one of the years it is active, even not after imputation of missing variables (see supra). Again, all observations for these firms must be deleted from our sample to avoid artificial entry and exit. Furthermore, the decomposition can not deal with firms that switch industries, therefore we delete all firms in the remaining sample that switch industries (6.000 firms). Finally, for a very small number of firms there are years in which the loglinear transformation of one of the variables of interest is negative, which raises problems in the calculation of TFP and the decompositions. After removing all these firms from our sample, we remain with a sample of about 109.000 firms. The last step is to clean our sample for measurement error. As detailed above, we clean our sample based on growth rate distributions of productivity and inputs. After this step, we remain a sample of about 80.000 firms that will be used for the MP and FHK decompositions. We would like to stress that the sole purpose of all these cleaning rules is to eliminate potential measurement error and to obtain a representative sample of firms that is suited for the decompositions. Also, we hope this approach to minimize potential biases in the covariance components of our decomposition, in which firm growth of market share and firm productivity growth serve as inputs, as these are key in answering our research questions. We are aware that this cleaning procedure is very stringent and reduces our sample drastically. Nonetheless, the cleaning rules we apply are objective from an empirical point of view. We loose a lot of observations because once a firm has negative value added for one year, we need to drop it because the log of a negative is not defined. We could have replaced negative value added by the average of its positive lagged and future value. However, doing so would result in artificial added value that was not created in reality. Especially in research on business cycles, this strategy is hard to defend. Of course, the same argument could be made against our cleaning procedure: the firms that are removed because they report negative value added are interesting themselves because they are the weak firms that may suffer most from recession periods and are cleansed out (see below). As with all empirical work, trade-offs must be made and we chose to limit ourselves to a sample about which we are confident that our statements based on the decompositions are correct.

For robustness check purposes, we also experimented with alternative samples in which we applied imputation and winsorization to retain more observations. The qualitative findings remain unchanged when we (i) impute annual accounts if firms did not report (ii) impute value added when it was negative, (iii) winsorize instead of drop outliers, (iii) include self-employed firms. Next to imputing value added for firms that report negative value added, we also looked at this group of firms separately since they are an interesting case themselves as one expects these firms to suffer most from recession periods and to be cleansed out afterwards. Since we cannot obtain TFP measures for firms with negative value added, we limit ourselves to discussing the evolution of the percentage of firms that reports negative value added and to the percentage of firms that report negative value added that exits. As can be seen in the figure below, the percentage of firms that reports negative value added increases in recession periods, however it did not fall back in the expansion period between 2002-2007. From the graph it is clear that the percentage of firms with negative value added that exit increases after the great recession. This insights adds to our findings on cleansing effects in the main body of the paper because this indicates that right after the recession, firms who are not able to create added value, are more likely to be cleansed out.



Notes: This graph shows the evolution of firms that report negative value added and the percentage of them that exit. It is not possible to include these firms in our sample since the productivity decompositions rely on loglinear TFP measures.

B.3.6 Production function estimates

The table below presents the production function coefficient estimates per industry. For an overview of the industry classification, see section B.4. As discussed in section B.3.1 of the appendix, the industry classification changed in 2006 from NACE rev. 1.1 to NACE rev. 2. This has consequences for the estimation of the production function and the decompositions at the industry level. Obviously, the same industry classification must be used for all years of the sample in order to estimate industry specific production functions or to do a productivity decomposition at the industry level. It is straightforward for firms that are active before and after the switch in the industry classification to put these into either one of the classifications since we have its code for each classification. The only assumption that is required, is that firms did not switch industries in the year that the classification structure changed. However, for firms that entered after 2006, no NACE rev. 1.1 code is known. Similarly, for firms that exit before 2006, no NACE rev. 2 code is known. Dropping these firms is a possible solution for the estimation of the production function, but it is not for the decompositions given our interest in entering and exiting firms. Therefore, we constructed a conversion from NACE rev. 1.1 to NACE rev. 2 based on the firms that report in both classifications. From these firms, we deduct which NACE rev. 1.1 to NACE rev. 2 two-digit combination has the highest frequency. This allows us to assign all observations to the NACE rev. 1.1 or the NACE rev. 2 classification. Although this maximizes the probability of assigning firms to the the correct classification, this remains an imperfect solution. Therefore, we aim to minimize the number of observations that must be assigned a NACE code based on our self-constructed conversion table. Since there are more firms in our sample for which only the NACE rev. 1.1 classification is available, we choose to proceed with the NACE rev. 1.1 classification both for the estimation of the production functions and for the productivity decompositions. The firms for which only a NACE rev. 2 code is available, are assigned the appropriate NACE rev. 1.1 code based on our self constructed conversion table.

Table A10: Value Added production function coefficient estimates

NACE (Rev.1.1)	Cobb Douglas Production Function		Translog Production Function		#firms
	Labor	Capital	Labor	Capital	
1t5	0.53	0.18	0.55	0.19	2412
10t12	0.62	0.05	0.64	0.08	364
13t14	0.61	0.11	0.62	0.14	420
15t16	0.71	0.10	0.75	0.11	3653
17	0.71	0.15	0.75	0.13	935
18t19	0.78	0.10	0.82	0.10	574
20	0.76	0.12	0.78	0.11	972
21	0.71	0.07	0.87	0.05	273
22	0.80	0.08	0.82	0.09	2411
23t24	0.79	0.08	0.82	0.06	643
25	0.80	0.04	0.83	0.06	674
26	0.77	0.07	0.79	0.06	1089
27	0.78	0.14	0.82	0.09	205
28	0.77	0.10	0.80	0.09	3665
29	0.84	0.06	0.87	0.06	1194
30t31	0.83	0.10	0.86	0.11	448
32	0.89	0.11	0.92	0.10	141
33	0.76	0.12	0.83	0.10	519
34t35	0.83	0.12	0.85	0.09	571
36	0.79	0.08	0.81	0.10	1475
37	0.64	0.19	0.65	0.19	329
40t45	0.77	0.10	0.56	0.28	27017
50	0.74	0.11	0.75	0.11	8479
51	0.78	0.09	0.81	0.10	20904
52	0.63	0.08	0.65	0.09	25528
55	0.65	0.09	0.68	0.10	15468
60	0.67	0.13	0.70	0.14	5398
61t62	0.79	0.12	0.72	0.16	163
63	0.78	0.07	0.82	0.06	2335
64	0.77	0.12	0.79	0.14	612
65t66	0.80	0.05	0.72	0.09	1926
67	0.69	0.07	0.68	0.09	4473
70	0.56	0.12	0.57	0.21	5823
71	0.53	0.15	0.55	0.18	1312
72	0.85	0.09	0.84	0.09	3857
73t74	0.74	0.08	0.72	0.10	22703
Total	0.73	0.10	0.75	0.11	168965

[a] The coefficient estimates are obtained from value added production functions following the Wooldridge (2009) estimator that relies on investments Olley and Pakes (1996) to proxy for unobserved productivity. This estimator is also robust to the Ackerberg et al. (2015) critique. More information on the estimation procedure can be found in appendix B.
[b] The output elasticities of translog production functions are firm specific. The fourth and fifth column of this table show the industry averages of these firm specific output elasticities.
[c] For some industries, the number of firms that can be used to estimate the production function is very small. This results in low variation and difficulties to obtain reliable estimates for the production function. Therefore, as can be seen in the table, for some industries a joint production function is assumed and estimated. For an overview of the classification, see B.4.
[d] All coefficient estimates are statistically significant at the five percent level.

B.4 NACE Rev. 1.1 Industry Classification

NACE-code	INDUSTRY NAME
	TOTAL MANUFACTURING
	Other production
1t5	Agriculture, hunting, forestry and fishing
10t14	Mining and quarrying
40t41	Electricity, gas and water supply
45	Construction
	Goods producing
15t16	Food products, beverages and tobacco
17	Textile and textile products
18t19	Textiles, textile products, leather and footwear
36	Manufacturing n.e.c.
37	Recycling
	Intermediate manufacturing
20	Wood and products of wood and cork
21	Pulp, paper, paper products
22	Publishing, printing and reproduction recorded media
23t24	Chemical, coke, refined petroleum and fuel
25	Rubber and plastic products
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products, except machinery and equipment
	Investment goods, excluding hightech
29	Machinery and equipment, n.e.c.
34t35	Transport Equipment
	Electrical machinery & post and communication services
30	Office machinery and computers
31	Electrical machinery n.e.c.
32	Radio, television and communication equipment
33	Medical, precision and optical instruments, watches and clocks
64	Post and telecommunications
	MARKET SERVICES, excluding post and telecommunications
	Distribution
50	Sale, maintenance and repair of motor vehicles and motrocycles; retail sale of fuel
51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
60	Land transport
61t62	Water and air transport
63	Supporting transport activities and travel agencies
55	*Hotels and Restaurants*
	Finance and business
65t66	Financial intermediation
67	Supporting activities to financial intermediation
70	Real estate activities
71	Renting of machinery and equipment
72	Computer and related activities
73t74	Research and development and other business activities

C Decomposition models

C.1 Dynamic Olley Pakes decomposition

The main body of the paper only includes the final equations from the decompositions. For completeness, we show how these equations come about. To decompose aggregate productivity growth between two periods, we start from the aggregate productivity levels in year one (TFP_1) and year two (TFP_2). In a dynamic context, surviving firms are defined as firms that are active both in period one and period two. Hence aggregate productivity of surviving firms shows up both in TFP_1 and TFP_2. Exiting firms are defined as firms that are in the sample in year one, but not in year two. Entering firms are firms that are not in the sample in year one, but are in the sample in year two. Therefore, aggregate productivity of exiting firms only shows up in TFP_1 while aggregate productivity of entering firms only shows up in TFP_2:

$$TFP_1 = MS_{S1} * TFP_{S1} + MS_{X1} * TFP_{X1} \tag{1}$$

$$TFP_2 = MS_{S2} * TFP_{S2} + MS_{E2} * TFP_{E2} \tag{2}$$

In which $TFP_{S1,2/X1,2/E1,2}$ denote weighted average productivity levels of surviving, exiting or entering firms in period one or two. $MS_{S1,2/X1,2/E1,2}$ is the aggregate market share of surviving, exiting or entering firms in year one or two. Since the sample in period one only consists of surviving and exiting firms and the sample in period two only consists of surviving and entering firms, the following equations hold:

$$MS_{S1} + MS_{X1} = 1 \rightarrow MS_{S1} = 1 - MS_{X1} \tag{3}$$

$$MS_{S2} + MS_{E2} = 1 \rightarrow MS_{S2} = 1 - MS_{E2} \tag{4}$$

Substituting (3) and (4) in (1) and (2) then results in:

$$\begin{aligned} TFP_1 &= (1 - MS_{X1}) * TFP_{S1} + MS_{X1} * TFP_{X1} \\ &= TFP_{S1} + MS_{X1} * (TFP_{X1} - TFP_{S1}) \end{aligned} \tag{5}$$

$$\begin{aligned} TFP_2 &= (1 - MS_{E2}) TFP_{S2} + MS_{E2} * TFP_{E2} \\ &= TFP_{S2} + MS_{E2} * (TFP_{E2} - TFP_{S2}) \end{aligned} \tag{6}$$

As is common practice in the literature, all these components are expressed in logarithms. Hence productivity growth in percentages can be obtained from subtracting (5) from (6):

$$\begin{aligned} \Delta TFP &= TFP_{S2} + MS_{E2} * (TFP_{E2} - TFP_{S2}) - TFP_{S1} - MS_{X1} * (TFP_{X1} - TFP_{S1}) \\ \Delta TFP &= \underbrace{TFP_{S2} - TFP_{S1}}_{\text{incumbents}} + \underbrace{MS_{E2} * (TFP_{E2} - TFP_{S2})}_{\text{entry}} + \underbrace{MS_{X1} * (TFP_{S1} - TFP_{X1})}_{\text{exit}} \end{aligned} \tag{7}$$

This equation shows how aggregate TFP growth can be decomposed into growth originating respectively from incumbents, entry and exit. *Surviving firms contribute positively if aggregate productivity of the surviving firms increases over time.* As surviving firms are active in both period one and period two, it is straightforward for this group of firms to look at the difference between aggregate productivity form period one to period two to infer the contribution of surviving firms to the change in aggregate productivity. *Entering firms contribute positively if aggregate productivity of the entering firms is higher than aggregate productivity of the surviving firms in period two.* When a firm enters the industry, this firm will only pop up in the aggregate productivity level the following period. Hence a change in aggregate productivity from period one to period two that results from entry will be picked up in aggregate productivity in period two, which is why equation (7) compares the aggregate productivity level of surviving and entering firms in period two to infer the contribution of entering firms to the change in aggregate productivity. *Exiting firms contribute positively if aggregate productivity of surviving firms is higher than aggregate productivity of exiting firms in period one.* If a firm with a low productivity level exits in period one, this will result in higher aggregate productivity in period two since the productivity level of the exiting firm is not included in the aggregate productivity level of period two. So productivity growth from period one to period two can result from firms with low productivity levels that exit in period one, which is why equation (7) compares the aggregate productivity level of surviving and exiting firms in period one to infer the contribution of exiting firms to the change in aggregate productivity. The reason why Melitz and Polanec (2015) claim this decomposition to be superior to earlier work from Baily et al. (1992), Griliches and Regev (1995) and Foster et al. (2001) is because of the intuitive counterfactual for entry and exit. This decomposition only shows a positive contribution from entry if entering firms show higher productivity levels than incumbents. Furthermore, there is only a positive contribution form exit if exiting firms exhibit lower productivity levels than incumbents. Other decomposition methods require to use the same counterfactual for the entry and exit components, which potentially results in biased contributions from entry and exit (see Melitz and Polanec (2015) for a further discussion on this topic).

While equation (7) allows to investigate the importance of entry and exit for aggregate productivity, it does not reflect the contribution of market share (re)allocation for aggregate productivity growth. To attain this, it is necessary to add the insight of Olley and Pakes (1996) to equation (7). They showed for a static context that any aggregate productivity measure can be decomposed into the sum of the uweighted average productivity level and the covariance between the productivity levels and the aggregation measure:

$$\begin{aligned}
TFP_t &= \textstyle\sum_i ms_{it} * tfp_{it} \\
&= \textstyle\sum_i (\overline{ms}_t + ms_{it} - \overline{ms}_t) * (\overline{tfp}_t + tfp_{it} - \overline{tfp}_t) \\
&= N_t * \overline{ms}_t * \overline{tfp}_t + \textstyle\sum_i (ms_{it} - \overline{ms}_t)(tfp_{it} - \overline{tfp}_t) \\
&= \overline{tfp}_t + \textstyle\sum_i (ms_{it} - \overline{ms}_t)(tfp_{it} - \overline{tfp}_t)
\end{aligned} \tag{8}$$

In which tfp_{it} and ms_{it} are productivity and market share of firm i in year t. $\overline{tfp}_t$ is the unweighted average of all firm level TFP estimates in year t and $\overline{ms}_t$ the unweighted average of all market shares in year t. The summation component of equation (8) is equal to the covariance between labor share and productivity. If this covariance is positive, then aggregate productivity is higher than it would be if labor shares were randomly allocated. So a higher covariance implies more efficient allocation of labor. Applying this transformation to the productivity components in equation (7) and rearranging the equation results in:

$$
\begin{aligned}
\Delta TFP = \quad & \underbrace{\overline{tfp}_{S2} - \overline{tfp}_{S1}}_{\Delta\overline{TFP}_{surv}} \\
& + \underbrace{\sum_i (ms_{iS2} - \overline{ms}_{S2})(tfp_{iS2} - \overline{tfp}_{S2}) - \sum_i (ms_{iS1} - \overline{ms}_{S1})(tfp_{iS1} - \overline{tfp}_{S1})}_{\Delta Cov(TFP,MS)_{surv}} \\
& + \underbrace{MS_{E2}\left[\overline{tfp}_{E2} - \overline{tfp}_{S2}\right]}_{\overline{TFP}_{entr_t - surv_t}} \\
& + \underbrace{MS_{E2}\left[\sum_i (ms_{iE2} - \overline{ms}_{E2})(tfp_{iE2} - \overline{tfp}_{E2}) - \sum_i (ms_{iS2} - \overline{ms}_{S2})(tfp_{iS2} - \overline{tfp}_{S2})\right]}_{Cov(TFP,MS)_{entr_t - surv_t}} \\
& + \underbrace{MS_{X1}\left[\overline{tfp}_{S1} - \overline{tfp}_{X1}\right]}_{\overline{TFP}_{surv_{t-1} - exit_{t-1}}} \\
& + \underbrace{MS_{X1}\left[\sum_i (ms_{iS1} - \overline{ms}_{S1})(tfp_{iS1} - \overline{tfp}_{S1}) - \sum_i (ms_{iX1} - \overline{ms}_{X1})(tfp_{iX1} - \overline{tfp}_{X1})\right]}_{Cov(TFP,MS)_{surv_{t-1} - exit_{t-1}}}
\end{aligned}
\tag{9}
$$

It is worthwile to discuss the intuition behind each of these components. $\Delta\overline{TFP}_{surv}$ refers to the evolution of unweighted average productivity in incumbent firms, i.e. a shift in the productivity distribution of incumbents. $\Delta Cov(TFP, MS)_{surv}$ refers to the growth in the covariance between market share and productivity for incumbent firms. This component is positive when one of the following actions takes place: (i) incumbent firms with higher than average productivity succeed in increasing their market share; (ii) incumbent firms with higher than average market share increase their productivity; (iii) incumbent firms with lower than average productivity loose market share; (iv) incumbent firms with lower than average market share become less productive. $\overline{TFP}_{entr_t - surv_t}$ refers to the difference in unweighted average productivity between entrants and incumbents. It shows whether the average entering firm is more or less productive than an average incumbent. $Cov(TFP, MS)_{entr_t - surv_t}$ refers to the difference in the covariances between entrants and incumbents. Thereby this component answers the question whether market share allocation is more efficient in entering firms than in incumbent firms. $\overline{TFP}_{surv_{t-1} - exit_{t-1}}$ refers to the difference in unweighted average productivity between surviving and exiting firms. So it shows whether the average exiting firm is more or less productive than an average incumbent. $Cov(TFP, MS)_{surv_{t-1} - exit_{t-1}}$ refers to the difference in the covariances between incumbents and exiting firms. As such this component learns whether market share allocation is more efficient in incumbents than in exiting firms.

As argued in the main body of the paper, a potential drawback of this approach is that the unit of observation is a firm i in year t. As a result, all components of the model abstract from the existence of markets at more disaggregated levels. So the model assumes all firms in the economy compete with each other, while it is more reasonable that firms are in closer competition with firms that are doing the same activity. Therefore, in a working paper version of Melitz and Polanec (2015) these authors enrich their model with an industry (disaggregated level) to sector (aggregate level) extension. This extension incorporates an additional industry dimension (j) in the model. All components of the extended model are calculated at the industry level and subsequently weighted averages of these components are constructed to obtain the outcomes at the aggregated level. However, this approach is inappropriate for the $\Delta Cov(TFP, MS)_{surv}$ component since market share can be gained or lost not only to firms in the own industry, but also gained or lost from or to firms in other industries. Therefore, the change in covariance at the aggregate level is not equal to the weighted average of changes in industry covariances. More specifically, an inter industry reallocation component must be added on top of this intra industry covariance channel in order the sum of all components to aggregate up to the change in aggregate sector productivity:

$$Cov(TFP, MS)_{surv,t} = \underbrace{\sum_j ns_{Sj} \sum_i (ms_{iSjt} - \overline{ms}_{jSt})(tfp_{iSjt} - \overline{tfp}_{jSt})}_{\text{Intra industry covariance}} + \underbrace{\sum_j (ms_{Sjt} - ns_{Sj})(tfp_{Sjt} - tfp_{St}))}_{\text{Inter industry covariance}} \quad (10)$$

In which the i, j and t subscripts refer to firm, industry and year. ns_{Sj} is the ratio of the number of surviving firms in the industry to the number of surviving firms at the aggregate level ($ns_{Sj} = n_{Sj}/n_S$). It is the weighting measure to construct aggregate intra industry covariance, which is defined as the weighted average of the industry level covariances between market shares and productivity.[1] Furthermore tfp_{jt} and tfp_t are respectively aggregate TFP at the industry and sector level.[2] The interpretation for the intra industry covariance is identical to the one of the $\Delta Cov(TFP, MS)_{surv}$ component from equation (9). The inter industry covariance is based on aggregate productivity levels instead of average productivity levels. It shows whether the aggregate market share of incumbents (relative to the market share expressed in number of surviving firms) is consistent with aggregate productivity of incumbents in industries. So the change in inter industry covariance for incumbents will be positive when one of the following actions takes place: (i) firms in industries with higher than overall aggregate productivity upsize, i.e. hire more employees; (ii) industries in which firms are large (in terms of employment) become more productive; (iii) firms in industries with lower than overall aggregate productivity downsize, i.e. dismiss employees; (iv) industries in which firms are small (in terms of employment) become less productive.

To make a similar distinction between the intra and inter industry contribution of entry and exit to the aggregate productivity evolution, the following decomposition is applied to the entry and exit components of equation (7):

$$TFP_{xt} - TFP_{yt} = \sum_j ms_j(tfp_{xjt} - tfp_{yjt}) + \sum_j ms_j((tfp_{yjt} - tfp_{xjt}) - (TFP_{yt} - TFP_{xt})) \quad (11)$$

With capital letters denoting productivity at the aggregate level and small letters denoting productivity at the industry level and x and y referring to S, E for the group of entering firms and to S and X for the group of exiting firms. Substituting equation (10) and (11) in equation (7) results in a decomposition that starts from the components at the industry level to obtain the aggregated sector level counterparts:

[1] It is inappropriate to use the same market shares for aggregation as for the calculation of the covariances. Otherwise it would not be possible to distinguish between a shift in the distribution (reflected by the change in average productivity) and reallocation.

[2] Aggregate productivity is always calculated as a weighted average.

$$
\begin{aligned}
\Delta TFP = \quad & \underbrace{\sum_j ns_j(\overline{tfp}_{Sj2} - \overline{tfp}_{Sj1})}_{\Delta\overline{TFP}_{surv}} \\
& + \underbrace{\sum_j ns_j \left[\sum_i (ms_{iSj2} - \overline{ms}_{Sj2})(tfp_{iSj2} - \overline{tfp}_{Sj2}) - \sum_i (ms_{iSj1} - \overline{ms}_{Sj1})(tfp_{iSj1} - \overline{tfp}_{Sj1})\right]}_{\Delta \text{ Intra ind } Cov(TFP,MS)_{surv}} \\
& + \underbrace{\sum_j (ms_{Sj2} - ns_{Sj})(tfp_{Sj2} - tfp_{S2}) - \sum_j (ms_{Sj1} - ns_{Sj})(tfp_{Sj1} - tfp_{S1})}_{\Delta \text{ Inter ind } Cov(TFP,MS)_{surv}} \\
& + \underbrace{\sum_j ms_{j2} * ms_{Ej2}(tfp_{Ej2} - tfp_{Sj2})}_{\text{Intra ind}_{entr_t - surv_t}} \\
& + \underbrace{\sum_j ms_{j2} * ms_{Ej2}\left[(tfp_{Sj2} - tfp_{Ej2}) - (TFP_{S2} - TFP_{E2})\right]}_{\text{Inter ind}_{entr_t - surv_t}} \\
& + \underbrace{\sum_j ms_{j1} * ms_{Xj1}(tfp_{Sj1} - tfp_{Xj1})}_{\text{Intra ind}_{surv_{t-1} - exit_{t-1}}} \\
& + \underbrace{\sum_j ms_{j1} * ms_{Xj1}\left[(tfp_{Xj1} - tfp_{Sj1}) - (TFP_{X1} - TFP_{S1})\right]}_{\text{Inter ind}_{surv_{t-1} - exit_{t-1}}}
\end{aligned}
\tag{12}
$$

For incumbent firms, this decomposition shows how much of the aggregate productivity evolution is caused by a shift of the distribution ($\Delta\overline{TFP}_{surv}$), how much intra industry reallocation of market share contributes to the aggregate productivity evolution (Δ Intra ind $Cov(TFP,MS)_{surv}$) and how important inter industry reallocation of market share is for productivity growth at the aggregate sector level. For entering and exiting firms the model shows how aggregate industry productivity premia of entering over surviving and surviving over exiting firms contribute to the aggregate productivity evolution (Intra $\text{ind}_{entr_t - surv_t}$ and Intra $\text{ind}_{surv_{t-1} - exit_{t-1}}$). Finally, Inter $\text{ind}_{entr_t - surv_t}$ and Inter $\text{ind}_{surv_{t-1} - exit_{t-1}}$ compare the aggregate industry productivity premia of surviving over entering firms and exiting over surviving firms with the aggregate sector productivity premia of surviving over entering and exiting over surviving firms.

C.2 Foster Haltiwanger Krizan

The main body of the paper discusses how decomposition models that start from tracking individual firms compare to decomposition models that start from the cross-sectional distribution of market shares and productivity.[3] We refer to the paper of MP for an extensive theoretical and empirical justification of this argument. As argued in the main body, we include the FHK decomposition because it allows us to distinguish productivity shocks and job reallocation, thereby it helps us to assess whether or not recession periods induce cleansing effects due to job reallocation. Moreover the FHK decomposition also serves as a robustness check for the entry and exit components. The contribution from the FHK decomposition to the discussion on cleansing effects of recessions is in the between-component (see infra). This between component regards changes in market share (job reallocation) while keeping the difference in productivity to the aggregate fixed. Thereby it rules out simultaneity in productivity changes and job reallocation:

$$
\begin{aligned}
\Delta TFP = \quad & \underbrace{\sum_i ms_{Si1}(tfp_{Si2} - tfp_{Si1})}_{\Delta \text{Within}_{surv}} \\
& + \underbrace{\sum_i (ms_{Si2} - ms_{Si1})(tfp_{Si1} - tfp_1)}_{\Delta \text{Between}_{surv}} \\
& + \underbrace{\sum_i (ms_{Si2} - ms_{Si1})(tfp_{Si2} - tfp_{Si1})}_{\Delta \text{Covariance}_{surv}} \\
& + \underbrace{\sum_i ms_{Ei2}(tfp_{Ei2} - tfp_1)}_{\text{Entry}} \\
& - \underbrace{\sum_i ms_{Xi1}(tfp_{Xi1} - tfp_1)}_{\text{Exit}}
\end{aligned}
\tag{13}
$$

[3] This distinction is also the reason why the FHK model at the aggregate can be calculated as a simple weighted average of the firm level components while the MP model cannot be constructed as a weighted average. In a cross section of a group of firms that are active in different industries there is inter-industry reallocation. This channel restricts one from expressing aggregate covariance as a weighted average of industry covariances. However, when you start the analysis from the firm level and only regard firm level dynamics, this channel is not identified.

Research Center for Regional Economics
Waaistraat 6 - bus 3550
3000 Leuven, Belgium

Jeroen Van den bosch

VIVES (KU Leuven)
jeroen.vandenbosch@kuleuven.be

Stijn Vanormelingen

ECON (KU Leuven, campus Brussels)
stijn.vanormelingen@kuleuven.be